Macroscopic emission modelling for urban networks

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Macroscopic Emission Modelling for Urban Networks

By

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An innovative methodology/framework has been proposed in this thesis for the effective application of well-known two-fluid model (TFM) on road emissions of urban networks to estimate the network-wide traffic-related emissions state at macroscopic level. This is demonstrated by developing an analytical model that illustrates the relationship between the parameters of the TFM and corresponding emissions of the traffic network. Hence the main contribution of this research study is the proposed hypothesis and consequently the formulation of a new model that estimates and evaluates the dynamic road emissions assessment at the network level in macroscopic manner. In addition, this study validates the feasibility of using the TFM to estimate vehicular emissions. The findings of the research are justified with two simulation experiments with two unique road networks. First network covers a part of Orlando downtown in United States, while the second network is artificial grid network with a number of roundabout intersections with uniform settings. Further investigations in this thesis were completed through empirical data collected from real case studies in order to discover the relation between the macroscopic fundamental diagram (MFD) properties (flow, density and speed) and road emissions.

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ABSTRACT

An innovative methodology/framework has been proposed in this thesis for the effective application of well-known two-fluid model (TFM) on road emissions of urban networks to estimate the network-wide traffic-related emissions state at macroscopic level. This is demonstrated by developing an analytical model that illustrates the relationship between the parameters of the TFM and corresponding emissions of the traffic network. Hence the main contribution of this research study is the proposed hypothesis and consequently the formulation of a new model that estimates and evaluates the dynamic road emissions assessment at the network level in macroscopic manner. In addition, this study validates the feasibility of using the TFM to estimate vehicular emissions. The findings of the research are justified with two simulation experiments with two unique road networks. First network covers a part of Orlando downtown in United States, while the second network is artificial grid network with a number of roundabout intersections with uniform settings. The research approach is to analyse the performance of traffic for entire network which include number of roads, links and intersections excluding examining the performance of traffic intersection separately. Further investigations in this thesis were completed through empirical data collected from real case studies in order to discover the relation between the macroscopic fundamental diagram (MFD) properties (flow, density and speed) and road emissions.

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Prophet Mohammed (Peace Be Upon Him) said:

"He who would not be thankful to people, he will not be thankful to ALLAH" (Reported by Tirmidhi)

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Chapter 1.

Introduction

1.1 Introduction

Transportation including air, land such as cable, rail and road, and water play a vital role in the social and economic development. Road transport is a fundamental element of the transport network to ease people and goods transportation. The increasing population, economic and business activities in global cities have rapidly raised the need to construct new roads, bridges, and other transportation facilities to accommodate rapidly increasing road traffic demands. Therefore, the number of motorised vehicles on roads has also increased. According to the World Health Organization (WHO), vehicle ownership in worldwide has increased by 16% over a three year period starting from 2012. The WHO report also stated that 67 million new passenger cars were introduced to world's roads in just one year in 2014 (WHO, 2015).

However, the increase of road transportation activities has inherent negative impacts as well and causes significant issues on the urban traffic such as air pollution, noise, traffic congestion and road accidents (Barth and Boriboonsomsin, 2008). During the past decade, motor vehicle emissions presented a serious challenge and have increased the environmental and public health concerns (Pascal et al., 2013). It is clearly accepted that transportation related emissions are major sources of air pollution, especially in urban areas (Transportation Research Board, 2002). For instance, the transportation related emissions in big cities are responsible for about 70% of air pollution in developing countries (WHO, 2015). Furthermore, a study showed that the travel delays in 471 urban areas across the United States caused significant increase in fuel consumption due to urban traffic congestion (Schrank et al., 2015). This raises the need for effective action to minimise the impact of air pollution through intensive studies to discover the sources of these pollution and current situation of air quality (European Environment Agency, 2015). However, air pollution is a challenging and complex problem with regards to air quality management and emissions mitigation (Brand et al., 2012).

1.2 Problem Statement

Vehicle emission models are essential tools to assess impacts of transportation activities and traffic management policies. Decision makers in the cities aim to minimise fuel consumption and emission of pollutants from traffic in addition to managing delays in the network. In order to achieve these goals, a reliable estimation of the traffic road emissions is essential. In general, traffic emission models are developed to represent the real-world situations through mathematical or physical relations between the operating conditions of vehicles and associated emissions (Zachariadis and Samaras, 1999; Ahn and Rakha, 2008). Typically, traffic emission models quantify the contaminants in two stages. The first step relates to the traffic parameters estimation with respect to traffic conditions and vehicle activities. The second step specifies factors that influence the emissions rate during different vehicle activities and traffic conditions.

Traffic emissions and fuel consumption models are typically classified into two main categories, microscopic and macroscopic, based on different complexity and the level of details needed for data collection. The microscopic emission models such as CMEM (Barth et al., 2004), PHEM (Zallinger et al.,

2005) and VERSIT+micro (Smit et al., 2007) have been developed by researchers to estimate road traffic emissions in an effective manner. Thus, more details have been taken into account with higher temporal and spatial resolution, considering the dynamics of individual vehicles (vehicle trajectories) traveling in the network (Demir et al., 2014) These models are also called dynamic models (Ahn, 1998).

However, the application of such model on large-scale networks is not worthwhile due to the requirement of enormous data as an input to the model, its corresponding cost and time needed for data processing and storing (Zachariadis and Samaras, 1997; Joumard, 1999; Boulter et al., 2007). Therefore, for large traffic networks, a microscopic vehicle emission model is not feasible and may cause undesirable result for traffic management. In general, they have been used for local and small networks to analyse the impact of driving behaviours on emissions.

On the other hand, the macroscopic emissions modelling have been developed to evaluate the traffic emissions in large-scale networks based on the average behaviour of vehicles in network. These models also estimate the related emissions for a given observations time and total distance travelled or the aggregated average speed. Such models do not require very large data sets to describe the dynamics of individual vehicles in the traffic network (Evans and Herman, 1978; Chang and Herman, 1981; Kouridis et al., 2000). For example, COPERT (Ntziachristos et al., 2009) and HBEFA (Keller et al., 2017) analysed traffic emissions based on the average speed of the traffic at different road links with several other assumptions, whereas the macroscopic model by (Csikós et al., 2015) was based on the total travel distance. Since they ignore the effect of other important factors such as the idling and cruising mode of the vehicles, the existing macroscopic emission models cannot provide accurate estimates for large-scale networks. This may cause issues for the accuracy of the results, especially in urban traffic areas with low speed conditions such as at traffic congestion or signalised intersections. Therefore, it is vital to develop more reliable emission estimation models based on the traffic parameters of a network.

In this study, a new approach is proposed to address limitations of existence average-speed-based models as discussed above, and consequently to obtain more reliable estimates of emissions. The proposed method incorporates additional traffic-related explanatory variables in order to develop a model to estimate the emission rates of vehicle in a large-scale transportation network in order to improve the accuracy of the results for urban traffic networks. Several studies exist in the literature to identify the sources of vehicular emissions and to investigate the factors that affect the amount of emissions. These studies emphasised on the importance of traffic-related factors for emission modelling. Hence, this research takes into account the effect of traffic parameters on emissions modelling in particular without considering the effect of other factors such as geometry-related (road grade) and environment-related (wind speed and temperature).

The two-fluid model (TFM) of traffic flow was developed by (Herman and Prigogine, 1979) in order to model the traffic in urban network and to address the difficulty associated with microscopic traffic modelling techniques. Some empirical studies (Herman and Prigogine, 1979; Ardekani, 1984; Herman et al., 1988) have shown that the two parameters of the TFM can be used as indicators of the performance of urban street networks. Recently, new technologies such as global positioning system (GPS) and smartphone applications have been used to collect detailed traffic data of a whole network. At the macroscopic level, the TFM estimates traffic parameters like traffic flow, speed, mean cruising, and stopping time with significant accuracy (Dixit and Geroliminis, 2015).

In the literature, the TFM model has been developed for different purposes such as evaluating the performance of traffic within an urban network at macroscopic level and analysing traffic safety measures. However, to the best of the author's knowledge, this model has never been used for modelling traffic emissions. Thus, this thesis aims to estimate the network traffic-related emissions with a macroscopic approach. The application of the TFM on road emissions of urban network has been offered through the proposition of a new methodology and framework.

1.3 Research Objectives

The main objective of this research is to develop a new approach for emissions modelling macroscopic level, to deliver reliable estimates of road traffic emissions.

The following are the sub-objectives of this thesis:

I. To develop a new methodology of estimating the road traffic air pollution of urban networks during different traffic conditions with respect to the average traffic variables. In addition, to utilise the traffic performance models at the network-level using the two-fluid modelling approach.

II. To demonstrate the application of the proposed model to estimate emission rate for Orlando downtown network in United States.

III. To investigate the accuracy of the proposed model in order to understand the relations between heterogeneity in density of specific network and vehicle emissions rate from simulation approach.

IV. To explore the relationship between the Macroscopic Fundamental Diagram (MFD) properties (flow, density and speed) and road emissions from field data that was gathered from road tunnel in Riyadh, the capital and the largest city of the Kingdom of Saudi Arabia (KSA).

In order to achieve the overall goal of this thesis and above-mentioned objectives, two different simulated traffic networks and a real-life dataset are utilised.

The first simulation network is the Orlando downtown network in the United States, which has about 107 signalised intersections over an area of around 2.7km ×2.7km. The second simulation network is a 6 x 6 grid network with several roundabout intersections having uniform settings and uniform loading throughout the network. In this approach, emissions model EnViVer, which is depend on the VERSIT+, is used to estimate the traffic emissions, based on second by second vehicle trajectories output from PTV VISSIM software. Since this study aimed to investigate the effect of traffic-related factors on emissions rate; we are not including all vehicles class and assumed that all vehicles during simulation belong to the same vehicle class. Passenger cars are chosen and represented as light-duty-city-2013 in the emissions model EnViVer.

Furthermore, real-world traffic and emissions data are collected from three different road tunnels located on Al Urubah road and Abu Bakr Al Siddiq road in Riyadh.

1.4 Thesis Outline

This thesis is divided into six chapters. An overview of each chapter of this thesis is presented below:

Chapter 2: Background

This chapter describes briefly the previous research particularly on the description and modelling of vehicular emissions. It then reviews several case studies that employed different modelling approaches to estimate traffic emissions. Lastly, this chapter reviews studies in the field of traffic flow modelling that are used to evaluate the large-scale network performance. The principal aim of this chapter is to identify the research gaps and to highlight the contribution of the proposed research in relation to previous research studies.

Chapter 3: Network Traffic Emission Model

This chapter demonstrates the development of the new methodology for estimating the traffic network emissions at a macro-level. The model assumptions and the data needed for each component are also introduced in this chapter. The application of the TFM on road emissions of urban network has been offered through the proposition of a new methodology and framework.

Chapter 4: Application of the Proposed Model in Orlando Network

The aim of this chapter is to present and describe the implementation of the model, as proposed in Chapter 3, on the Orlando downtown network in the United States. VISSIM micro-simulation software and EnViVer have been used for this purpose. In addition, calibration of conventional macroscopic speed-flow models on network-wide to identify the best estimation model of MFD.

Chapter 5: Empirical Analyses of the Proposed Model in a Grid Network

This chapter discusses the results from the micro-simulation of a grid network with various levels of traffic density. It also explores the impact of network heterogeneity on total emissions rate of vehicles. In addition, an error analysis has been conducted to compare the results from the proposed model with data simulated on the microscopic emission model.

Chapter 6: The MFD and Vehicular Emission Relationship

This chapter presents and describes the real-world datasets, i.e., three different tunnels located on Al Urubah and Abu Bakr Al Siddiq roads in Riyadh. This chapter investigates the relationships between macroscopic traffic parameters (flow, density and speed) and road emissions as well.

Chapter 7: Conclusions and Future Directions

This chapter summarises the thesis and discusses the key findings from the research. Furthermore, the limitations of the current research work are also highlighted with a few potential future extensions of the research work.

Chapter 2.

Background

As mentioned earlier, vehicular emissions are a major contributor towards urban air pollution. The rapid rise in vehicle ownership and vehicle kilometres travelled, have led to an increase in the fuel consumption and the resulting vehicular emissions. Environmental impact assessment has become one of the main criteria for evaluating traffic control strategies in urban networks. Transportation decision-making in urban area aims to minimise the total emission emitted from vehicles in addition to managing the total tip time in traffic system. A vehicle emission modelling is a fundamental tool to evaluate the impact of traffic activity on air quality. Already abundant research has been conducted in the area of modelling vehicular emissions.

Beginning with vehicular emissions, this chapter reviews the existing research and methods in traffic emission with the conventional vehicle emissions measures. Then, macroscopic traffic models, which have been used to evaluate the large-scale network performance, are discussed in this chapter. In addition, a critical evaluation of the previous study is presented to identify the significance of this research.

2.1 Vehicular Emissions

This section is divided into a few sub-sections to discuss different aspects in vehicular emissions in detail:

2.1.1 Sources of Vehicular Emissions

The emission from vehicles generally can be divided into two groups. One of them is called exhaust emissions, which is a by-product of combustion process of fossil fuels; another one is called non- exhaust emissions.

1. Exhaust Emissions

Exhaust emissions are all substances emitted to air as a by-product of combustion process of fossil fuels such as petrol, diesel, and natural gas (NG) and liquefied petroleum gas (LPG) when vehicle engine is running. They are of two types:

- *Start-up emissions:* emissions when the engine of vehicle is started after been turned off whether the engine is hot or cold.
- *Running emissions:* emissions when the engine of vehicle is running including idling mode.

2. Non- Exhaust Emissions

These include emissions generated from fossil fuel losses due to evaporation, tyre and brake wear and road surface wear.

2.1.2 Main Motor Vehicle Emissions

This section is a brief background on pollutants emissions from vehicles, and discusses their effect on environment and human health. A variety of pollutants are generated during fuel combustion process. The major pollutants released from vehicles are as follows:

Carbon Monoxide (CO) is a colourless, odourless, and tasteless poisonous gas and is formed as a by-product of incomplete combustion of fossil fuels such as gasoline especially at low temperatures or low air-to-fuel ratio. Diesel engines generally emit lower amount of CO than gasoline engines. High level of CO can lead to headache, dizziness and even death (EPA, 2008a). Vehicular emissions contribute about 60 % of all CO emissions in the United States and 95% of all CO in cities (EPA, 2012).

Nitrogen Oxides (NOx) are the generic name for NO, NO_2 and other nitrogen oxides. They are formed during combustion of fossil fuels under high pressure and temperature conditions. Diesel engines emit higher amounts of NOx than gasoline engines due to their high combustion temperatures level. Many of the nitrogen oxides are colourless, odourless and relatively non-poisonous gases. Except for NO_2, which is extremely poisonous, has a distinct odour and can be seen in brown colour. In general, NOx gases mainly contribute to the formation of ozone and acid rain. According to US EPA estimate, the mobile sources contribute about 31 % of all NOx emissions in the United States (EPA, 2012).

Hydrocarbons (HC) are produced from incomplete combustion of fossil fuels or from fuel evaporation. HC reacts with the sunlight causing smoke and ground level ozone formation. HC emissions from on-road mobile sources generated 29% of the total HC emitted in the United States (EPA, 2013).

Particulate Matter (PM) is the common term for all organic and inorganic particles that get suspended in the air from motor vehicles such as resuspended road dust, smoke, and liquid droplets. They are usually classified into PM10 and PM2.5 based on their size. High level of PM concentrations can cause health problems, including lung cancer and heart diseases. In addition, PM harms the environment and causes erosion and staining of structures as well as reduction in visibility. Diesel engines emit significantly higher amounts of PM than gasoline engines. The EPA report that on-road mobile sources contribute 10% of the total PM2.5 in United States, of which 72% of this is produced by diesel vehicles (Hodan and Barnard, 2004).

Carbon Dioxide (CO_2) is produced from complete combustion of fossil fuels. CO_2 is not considered as a pollutant form motor vehicles; therefore it does not directly harm human health. However, it is a main greenhouse gas, which causes global warming. According to US EPA estimate, on-road mobile sources are responsible for over 30% of the total CO_2 emissions in the United States (EPA, 2013).

Sulphur Oxides (SO_x) is produced from sulphur burning during combustion of fossil fuels. Diesel engines emit more SO_2 than gasoline engines since diesel contain higher Sulphur.

For more information on motor vehicle emissions, which is not actually covered in this section, we refer to United States Environmental Protection Agency (EPA)'s website [www.epa.gov] that provides a very intensive database of documents and reports regarding on-road emissions and their effect on health and air quality.

It should be noted that CO_2 is the main source of emissions of greenhouse gases (GHGs) with regards to global climate change, and it is been considered as one of the main issues for environment and global warming. Therefore, the traffic-related CO_2 emissions are the focus of this study and used as air quality index to evaluate the impact of traffic. However, our proposed methodology and framework can be easily applied to evaluate other type of pollutants.

2.1.3 Factors Affecting Transportation Pollutants

Several analyses have been conducted in the literature to identify the main factors that contribute to the rise in vehicular emissions. The majority of these factors are found to be traffic related. However, In order to have accurate estimates of emissions from on-road vehicles, it is important to consider the variable and parameters that influence emissions. These parameters can be grouped as follows (Hassounah and Miller, 1994; Abbott et al., 1995):

Traffic-Related Factors: Traffic characteristics such as the level of traffic congestion, number of stops, lane change maneuvers, and distance travelled are the major traffic related factors affecting emissions. The driving modes such as idling, cruising, acceleration and deceleration basically form the shape of driving cycle of vehicles, which have clear impact on emission rates for same distance travelled (Zhang et al., 2011).

Driver-Related Factors: The behaviour of the drivers and degree of aggressiveness has clear influence on speed and acceleration. For instance, frequency and sharp accelerations during lane change and overtaking decrease the efficiency of engine combustion of fossil fuels. Therefore, more fuel is consumed leading to more emissions (Brundell-Freij and Ericsson, 2005).

Vehicle-Related Factors: Vehicle characteristics and manufacturing technology such as vehicle weight, engine size, engine fuel type, and transmissions type are factors influencing the amount of emissions to the air. Although, the maintenance of vehicles is important to maintain fuel consumption level, the old vehicles produce more emissions. In addition, vehicle status such as mileage and mechanical status are important parameters that influence emissions (Faiz et al., 1996).

External Factors: These factors include highway network characteristics (grade, curves, pavement quality, and meteorological conditions) and environment conditions such as temperature, pressure, and humidity (Flagan and Seinfeld, 2012) .

It should be noted that several studies in the literature have been conducted to identify the sources of vehicular emissions and investigate the factors that affect the amount of emissions. They found that the main role is played by traffic-related factors (Ding, 2000). Hence, the basic idea of this research is taking into account in particular the effect of traffic-related factors on emissions modelling, while the effect of other factors is neglected such as geometry-related (road grade) and environment-related (wind speed and temperature). In addition, this study has chosen passenger cars to represent all vehicles classes in a network. However, the proposed methodology can be easily applied to different types of vehicles classes.

2.1.4 Vehicle Emission Measurements

There are several techniques to measure emissions from vehicles. The main difference among the methods is the purposes of testing, variety of equipment cost and accuracy can be used for different purposes and applications (Ropkins et al., 2009). Vehicle emission measurements are critically important to test the validity of the environmental prediction models by campaigns to field measurements. For environmental impact assessment purposes, the mass emission measurements are expressed as either emission rate (g/sec) or emissions factors (g/veh-km). The most commonly used procedures are as follows:

2.1.4.1 *Laboratory Tests*

Laboratory measurements of vehicular emissions generally provide the highest possible accuracy and repeatability, based on very complex and advanced equipment called “chassis dynamometer” (Figure 2.1). Generally, emission rates are calculated on the chassis dynamometer by operating the vehicle through pre-defined cycles of accelerations, decelerations, speeds, and idling that reflect real-world performance. Despite driving cycle do not fully characterise real-world driving patterns; it is an important tool to improve the accuracy of predictive models. In addition, the laboratory test procedures are used for vehicle emission certification and other emission regulation. For example, the US FTP-75 emission test cycle by the California Air Resources Board (CARB) is used to define the level of emissions that car can emit for vehicle categories with respect to emissions standard, i.e., LEV, ULEV, etc.

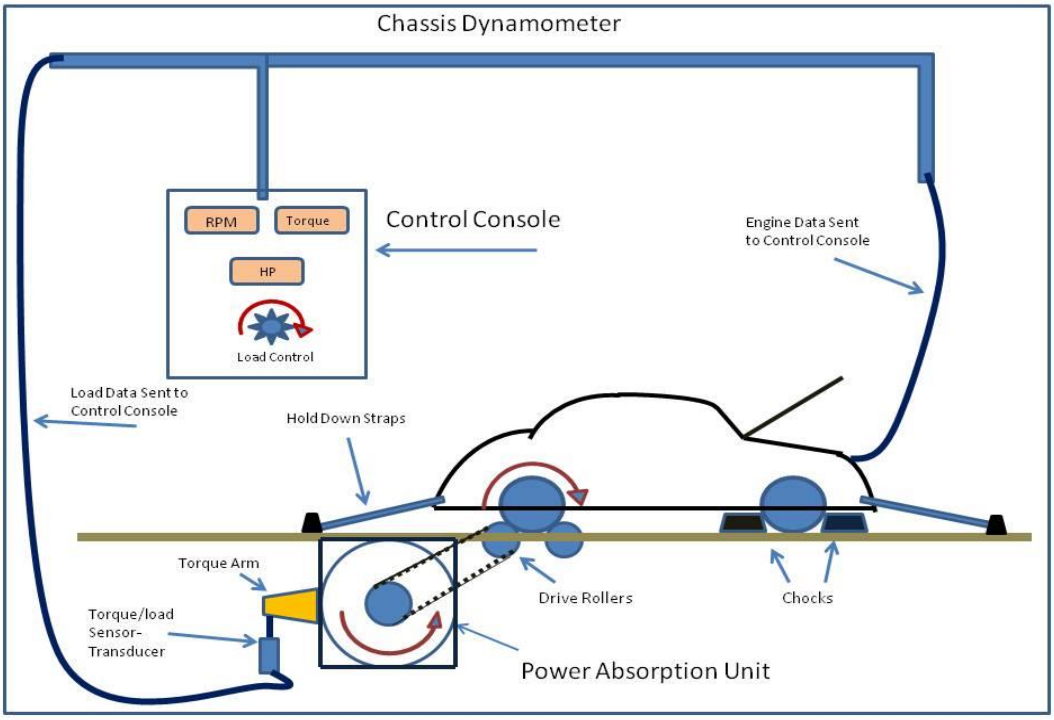


Figure 2.1: Chassis Dynamometer

(From http://www.ecologiclabs.com/chassis-dynamometer-testing)

2.1.4.2 *Field Testing*

1. *On-Vehicle Measurement*

A very first on-board emission test equipment was introduced in the late 1990s (Jetter et al., 2000). The unit, which is called *Portable Emission Measurement Systems* (PEMS), can be installed on a vehicle to directly measure the emissions from vehicles during driving on the road (Figure 2.2). The result of PEMS test is primarily subjected to the vehicle's test conditions. The PEMS systems measure real life emissions from individual vehicle with high level of accuracy as compared with laboratory test. In addition, there is still some variation between emissions measured in laboratory tests and the real life. This is because driving cycles do not reflect all differences in driving conditions, such as driving behaviour, traffic and weather conditions. However, the on-board test does not replace the laboratory test, but complements it.

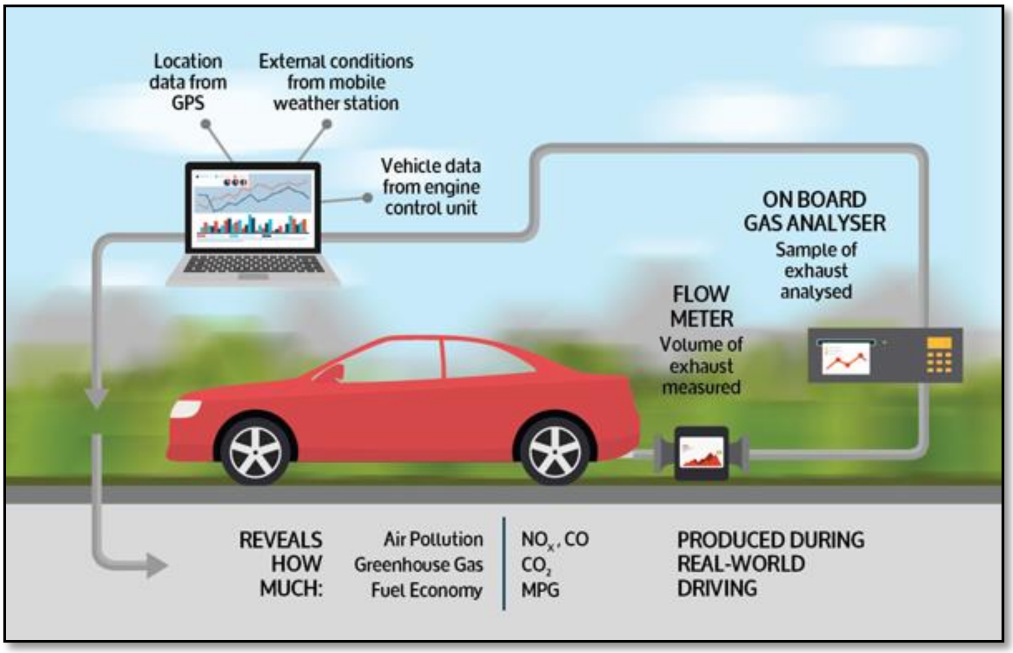


Figure 2.2: Main Components of Portable Emissions Test

(From http://emissionsanalytics.com/pems-testing/)

Recently, a new Real Driving Emissions (RDE) test procedure using PEMS has been introduced by European Commission to address the limitation of laboratory test and verify the emissions rate during a wide range of real operating conditions on the road (Giechaskiel et al., 2016). In addition, the RDE test helps to ensure that cars are classified as low-emission vehicle deliver low pollutant emissions on the road similar to the laboratory test.

2. *Remote Emission Measurement*

The remote sensing (RS) technique measures exhaust emissions introduced in the late 1980s (Bishop et al., 1989). In many purposes of testing, vehicle emission remote sensing is complementary to both PEMS and Laboratory testing. Emissions are measured remotely from the side of the road to present the whole fleet average emission performance. Vehicle operating conditions are not predetermined or unaware of the emission test. However, remote emission testing methods are used to facilitate real air quality monitoring and control of emissions from motor vehicles.

There are a few limitations of remote sensing technique with respect to vehicle emissions measurement (Borken-Kleefeld and Dallmann, 2018). For example, weather conditions highly affect the result from remote sensing, e.g., measurements are more difficult to conduct when raining or on a wet surface. Another limitation is that the emissions remote sensing measurements are not sensitive to idling mode, so emissions corresponding to idle are not captured. Moreover, remote sensing is fixed monitoring network, so target sampling is spatially fixed (Figure 2.3).

In conclusion, variety of measuring techniques used to monitor and control vehicular emissions in order to avoid the pollutant concentrations from exceeding the air quality standards. In general, vehicle emission measurements discussed above provide an accurate quantification of pollutants from all sources of vehicular emissions and they are essential tools to emissions inventories and model development.

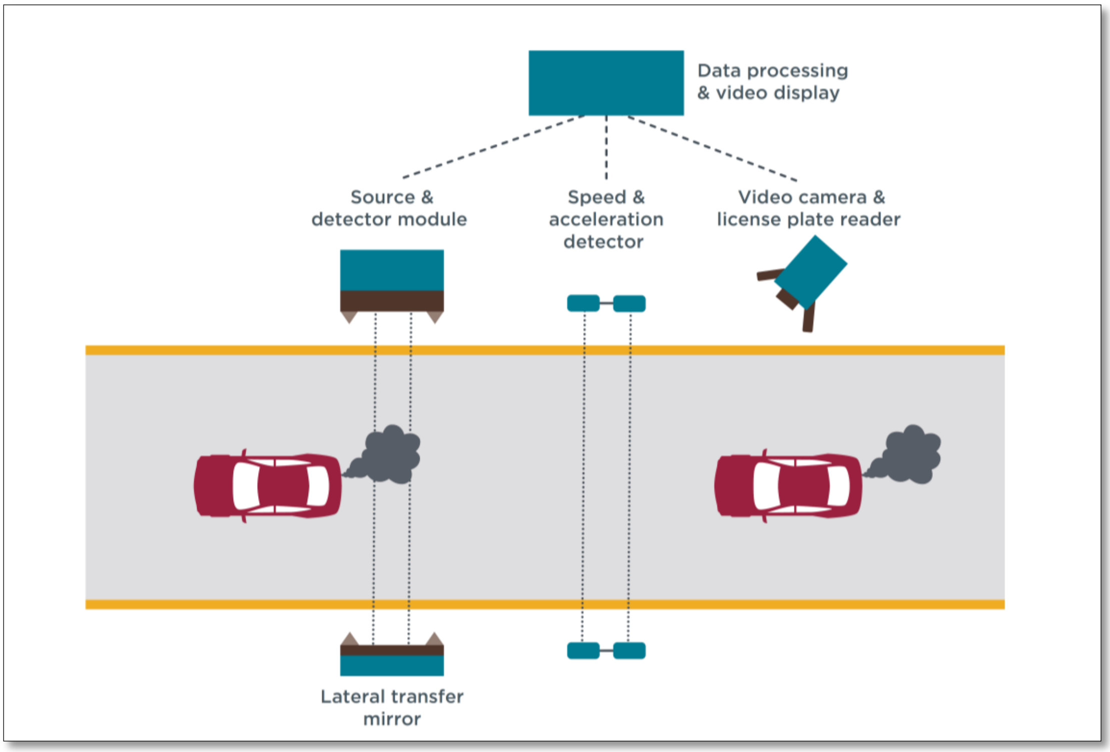


Figure 2.3: Main Three Unit of Remote Sensing Method
(Borken-Kleefeld and Dallmann, 2018)

2.1.5 Vehicle Emissions Modelling

Traffic emission models are essential in transportation planning and control since they facilitate air quality and environmental impacts studies to evaluate proposed strategies from traffic engineers. Traffic emission models provide the estimate or prediction of mobile source emission based on the operating conditions of the vehicles in traffic flow.

In general, the common emission-modelling framework is usually effective in three steps. The first step is to identify the input variables representing traffic or vehicles performances considering the spatial and temporal resolutions. For example, some model require the average speed as main input to the model (Akcelik, 1985), or instantaneous speed and accelerations (Ahn et al., 2002; Liu, 2005), while other models are vehicle specific power (VSP) approach, based on second-by-second engine power required per vehicle unit mass and fuel demand (Jimenez-Palacios, 1998; Zhai et al., 2008). The second step is to calculate the emission rate associated with input data with respect to other parameters affecting the magnitude such as vehicle-related factors. This step is to define the set of emission factors that determine the level of emissions rate. For instance, the idling emission rate for different vehicles varies significantly and the amount of pollutants released increases as the gross vehicle weight increases (EPA, 2008b). In addition, some models include the external effects in emission prediction such as weather conditions, geometric design of the road. For instance, the vehicle emission rate also depends on the road grade because the vehicles require additional engine power to meet the increased load resistance to maintain the same speeds (Zhang and Frey, 2006; Prati et al., 2014). Finally, the quantity of the emission factor (g/km) and the emission inventory (g/step-time) can be obtained, and the amount emissions during sampling periods are the product of the results of these two steps together.

In conclusion, similar to traffic flow models, traffic emission models also differ based on the modelling approaches used. Emission models can be developed either for individual vehicle and quantify pollutant rate directly based on vehicle behaviour, or developed to estimate the emissions rate with regards to average behaviour of vehicles based on link level or network level. Generally, based on the resolution of the input variable (traffic data), the emissions model can be classified into two main categories, microscopic models, and macroscopic models (Yue, 2008). Macroscopic models calculate network-wide emissions rates by using aggregated variables temporally and spatially, such as vehicle kilometres travelled (VKT) and average speed. Microscopic models estimate emissions with higher spatial and temporal level and considering individual vehicle activity.

2.1.5.1 *Microscopic Emission Models*

Microscopic emission models provide instantaneous emissions estimation based on instantaneous vehicle operating and road conditions. Second-by-second vehicle trajectories and road characteristics are main input variables to estimate emission in these models. Examples of microscopic emission models are follows:

a. Comprehensive Modal Emissions Model

Comprehensive modal emissions model (CMEM) is developed at the University of California at Riverside and the University of Michigan in August 1995 (An et al., 1997). This model is power-demand model that estimates emissions based on empirical approach and contains six modules, including engine power, engine speed, air/fuel ratio, fuel use, engine-out emissions, and catalyst pass fraction. Figure 2.4 shows basic layout of CMEM Architecture.

CMEM has been developed based on a very large real emission database collected every second from 300 vehicles using the chassis dynamometer to measure the tailpipe emission rates. The test was performed with three driving cycles, i.e., FTP cycle, US06 cycle and Modal Emission Cycle (MEC). The CMEM model can estimate the tailpipe emissions second-by-second based on second-by-second speed and acceleration from vehicle trajectories. However, the heavy duty vehicles such as trucks and buses are not included in comprehensive modal emission model as well as unable to estimate particulate matter. In addition, the result from CMEM model is based on laboratory test approach and may not represent the real operating conditions on the road (Faris et al., 2011).

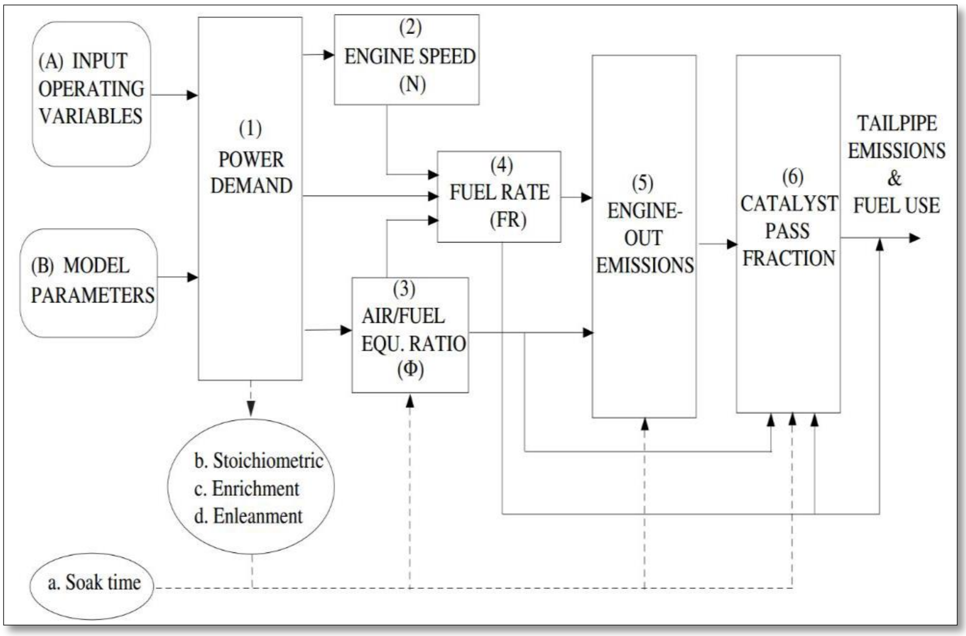


Figure 2.4: Modal Emissions Structure of CMEM (George and Matthew, 2006)

b. VT-Microscopic Model

This model is developed by Rakha and Ahn to predict the instantaneous fuel consumption and emission rates of individual vehicles based on their instantaneous speed and acceleration levels (Ahn et al., 2002; Rakha et al., 2000). The VT-Micro is a multiple regression model with various polynomial combinations of speed and acceleration components. The model was tested with multiple driving cycles using chassis dynamometer data collected at the Oak Ridge National Laboratory (ORNL) (Rakha et al., 2004). The main input variables to this model are the driving pattern of individual vehicles with instantaneous speed and acceleration. The model can be described mathematically as follows:

$$MOE_e = \sum_{i=0}^{3}\sum_{j=0}^{3} \exp(k_{i,j}^{e} * v_{VT}^{i} * a^{j}), for\ a \geq 0 \tag{2.1}$$

$$MOE_e = \sum_{i=0}^{3}\sum_{j=0}^{3} \exp(l_{i,j}^{e} * v_{VT}^{i} * a^{j}), for\ a \leq 0 \qquad (2.2)$$

The VT-Micro is sensitive to the vehicle driving modes including idling, cruising, accelerating and decelerating conditions, especially when it used to estimates the CO emissions. (Rakha et al., 2004) also show that the model can be used with instantaneous speed measurements from GPS data to estimate vehicle emissions. Although, the VT-microscopic model estimates vehicle fuel consumption within 2.5% accuracy when comparing to actual field measurement, the model provides unexplainable mathematical result in emissions predictions. Furthermore, the calibration process of the models comprises 32 coefficients, which may cause misleading results because the model may overfit the data.

c. VERSIT+Micro

This model is developed at the Netherlands by Netherlands Organisation for Applied Scientific Research (TNO) to simulate the traffic emissions as well as energy consumed. The TNO data include emissions from around 2,800 cars measured in various conditions (Smit et al., 2007). The VERSIT+ is statistical model that calculates the emissions based on second by second vehicles trajectories and the main input variables are speed and acceleration of individual vehicle. Despite that the effect of the speed on the emission estimates is limited, the model yields high accuracy result for various vehicle types and take into account the effects of traffic conditions, thus the model help for real time environmental monitoring and assessment. This is because the relation between speed and emissions rate is linear (Faris et al., 2011).

VISSIM simulation model has an environmental modelling package called EnViVer, which integrates the microscopic emission model (VERSIT+) into

VISSIM microscopic simulation (Eijk and Ligterink, 2014). The EnViVer provides a simple user interface that eases the use of this simulator for environmental assessments. The model calculates PM10, NOx, CO_2 emissions on detailed level for different time and spatial selection, with wide range of selecting vehicle types or fleets. In addition, the result from simulator after emission calculation performed can be formatted in emissions file with detailed simulation results or GIS format output.

d. MOVES

EPA's Motor Vehicle Emission Simulator (MOVES) is mission model that estimates emissions for mobile sources at different scales, macroscopic such national and county, and project level as microscopic level. The project level of MOVES is a load-based emissions mode which estimates instantaneous emissions rate associated with second-by-second movements of each individual vehicle (Koupal, and Cumberworth, 2010). As shown in Figure 2.5, MOVES model first calculates the total time spent in idling, acceleration, deceleration, and cruising by each vehicle, considering the change in engine power, engine speed and fuel rate. Then, the model estimates the vehicles emission rate for different operating modes. This model requires a wide range of user-defined conditions such as he geometry of the road, the vehicle parameters (EPA, 2014).

The key drawback of the MOVES is that the model relatively requires higher time due to high complexity of computation. This is because the model requires identification of specific parameters of each vehicle. In addition, the use of MOVES in the project-level feature of real-time emission monitoring is relatively limited and slow due to the intensive database required by the model. Moreover, the accuracy of MOVES at project level is not high comparatively (Faris et al., 2011).

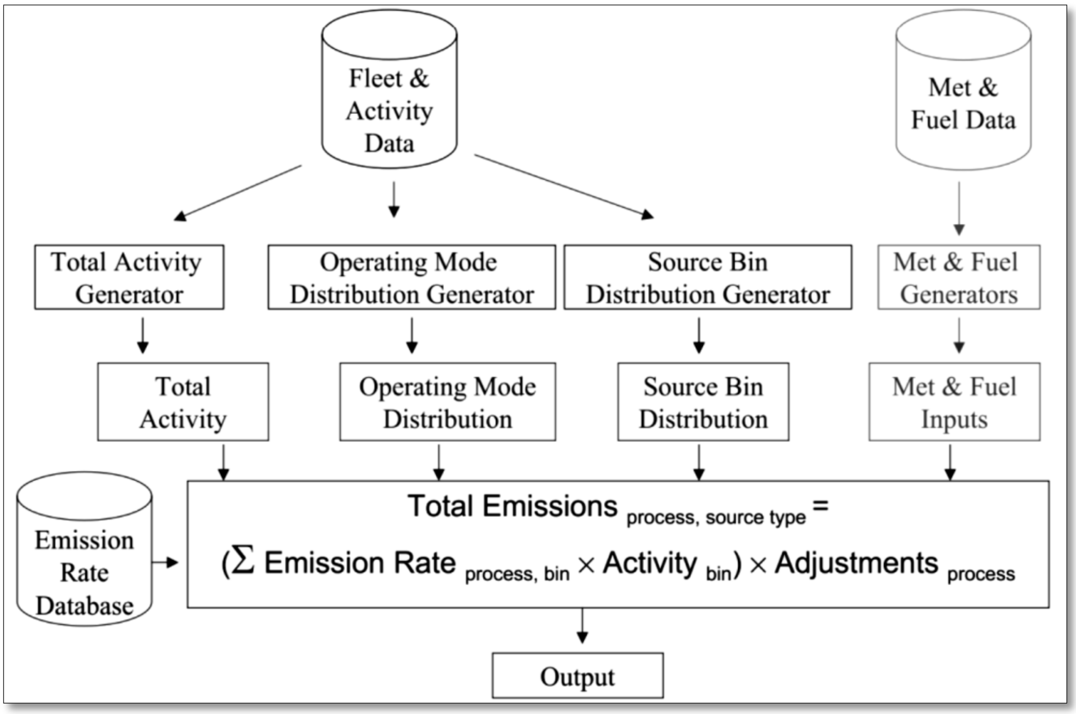


Figure 2.5: General Model Framework of MOVES ((Jing et al., 2014)

2.1.5.2 *Macroscopic Emission Models*

Macroscopic emission models use the aggregated traffic parameters (flow, density and speed) to estimate urban network emissions on a large-scale network. In most cases, the average speed of vehicles is used as the effective traffic parameter representing the traffic conditions. Macroscopic emission models are generally used in applications on a large spatial scale, such as national and regional emissions inventories. The key models in the macroscopic vehicle emissions modelling include:

a. COPERT

The macroscopic emission model COPERT is computer software to calculate emissions from road transport average activities. The model is based on linear regression of vehicles average speed and the measured emission factors (g/km) (Ntziachristos and Samaras, 2016). The model was developed by

European Environment Agency and widely used in many European countries. In addition COPERT estimates the total hydrocarbon emissions due to fuel and the emissions related to cold-start of vehicle engine. The model can be applied to calculate traffic-related pollutants for rural and urban areas using range of pre-defined driving cycles produced to assess the performance of vehicles in Europe.

In this model, individual vehicles activities are not considered. Average speed model estimates emissions for traffic network in large-scale using average speed of vehicles as aggregated level of traffic parameter that represent the traffic conditions. Flowing is one of the most used formats of average-speed-based model:

$$Ei = \sum_{c}\sum_{l} VKM \times fc \times \mathrm{BERi}\ (\mathrm{s\bar{l}}, \mathrm{c}) \qquad (2.3)$$

Where:

Ei : is the total emission of the species i,

c : is the vehicle category of interest,

l : is the sub-region of interest where the average speed of vehicles is $s\bar{l}$,

VKT : is the vehicle kilometres travelled in a given network and period of time,

fc : is the fraction of vehicles of category c to total number of vehicles,

$BERi\ (s\bar{l}, c)$: is the Base Emissions Rate per distance (km or mile) for the emissions species i, associated with vehicle category c and average speed of $s\bar{l}$ in the sub-region l.

The model estimates wide range of pollutant sources from transport, such as cold start emissions, hot emissions, tire and brake wear emissions and fuel evaporation. However, there are some problematic validations especially with CO and HC since COPERT overestimate the result with more than 30 % (Oduro, 2016).

b. Watson Model

Watson (1979) developed model to estimate fuel consumption using average speed. The effect of different positive kinetic energy during acceleration is integrated to the proposed model.

$$F = K_1 + {K_2}/{V_s} + K_3 V_s + K_4 PKE \tag{2.4}$$

Where the value of positive kinetic energy (PKE) changes represents due to difference in acceleration as shown:

$$PKE = \sum \left(V_f^2 - V_i^2\right)/(12.960\ X_s) \tag{2.5}$$

The model calculates the fuel consumption based on average trips, initial and final speed and total distance travelled. The Watson model estimates fuel consumption with reasonable accuracy in comparison with instantaneous speed-based models. In additions, this model is applicable to average speeds of less than 55 km/h in order to limit the aerodynamic effect (Evans et al., 1976; Evans and Herman, 1978).

c. EMFAC

The EMFAC model is another vehicle emission model that estimates mission rate based on vehicle average speed. The model is macro-simulation software that has been widely used for transportation planning in California in the USA. This model is developed by California Air Resources Board to estimate wide range of pollutants, i.e., HC, CO, NOx, CO2, and PM and fuel consumption (EMFAC 2014, 2015). The model uses the data obtained from the dynamometer drive cycle from thirteen various vehicles types included passenger cars, types of trucks and buses and motorcycles to develop regional emissions inventories. EMFAC can model traffic source emissions for multiple temporal and spatial resolutions. The key drawback of the EMFAC is that it ignores effect of the traffic signal coordination (Faris et al., 2011).

2.1.6 Trends in Network Emissions Modelling

The micro-level models provide more accurate fuel consumption and emission estimation. However, this kind of model can require very intensive data collection and complicated to be used for network-wide emissions estimation due to intensive computational effort. In addition, the application of the microscopic emission models on large urban networks is not feasible due to the difficulty of tracking second-by-second vehicles movements in network. Furthermore, the detailed trajectories with corresponding emissions may not be very beneficial in large-scale urban decision making and planning. In comparison, the average speed models generally measure emission rate based on trip speed, so such models require less data and calculation time. However, they do not include the effect of changes in operating modes. Therefore, there is a need to develop a macroscopic emission model based on multimodal evaluations for larger urban networks.

Nesamani (2007) developed a model that estimates emission of road link based on vehicle speeds by considering a set of Emission Specific Characteristics for each link. The emission model is based on empirical measurements using multiple linear regressions and instantaneous speed and acceleration of the vehicle from a traffic simulation model. The result shows that traffic management and control strategies based on average speed have failed to achieve significant reductions on pollutant emissions, so other traffic variables should be included in the environmental impact analysis.

Shabihkhani and Gonzales (2013) proposed an analytical approach based on kinematic wave theory to estimate emissions at signalised intersections. The model is capable enough with feasible accuracy to estimate number of stops and time spent idling and cruising based on the arrival rate of vehicles. The result shows that total emissions can be estimated easily based on the proposed analytical traffic model, using less data as compared with micro-simulations.

Salamati (2015) developed an empirical approach based macroscopic model to investigate the effect of congestion on roundabouts and signalised intersections in vehicular emissions. The model based on Vehicle Specific Power variables and explanatory traffic variables, including intersection capacity, number of lanes, demand-to-capacity ratio, and green-to-cycle length ratio and signal progression characteristics. Their study showed that under low demand-to-capacity ratios, roundabouts generally produce less emission than signalised intersections. However, when demand approaches capacity, the emission rates are lower at signalised intersections than roundabouts.

Chen (2016) also proposed an analytical approach based on macroscopic traffic parameters. The model has used MOVES operating mode distribution methodology and the result from microsimulation by means of stepwise regression. The main inputs to the model are vehicles travelled distance and time delay in order to estimate emissions. The result shows that the model is more accurate than operating mode models.

2.2 Traffic Flow Modelling

It is pretty clear that reliable estimation of traffic parameters is essential in order to model traffic emissions. Traffic flow models illustrate the traffic streams to evaluate the traffic performance in intersections, single road or network. Based on the level of aggregation, traffic models are categorised as microscopic and macroscopic traffic flow models. There are also developments that combine some of the characteristics of macroscopic models and some characteristics of microscopic models called mesoscopic traffic models (Hoogendoorn and Bovy, 2001).

Macroscopic models are an aggregation of the vehicles' activities and are used to evaluate the large-scale network performance. They are based on the average activities of the traffic in road without describing the dynamics of individual vehicles' behaviour in the traffic network. Macro model require average traffic flow characteristics in network such as average flow, density, speed, idling time and cruising time. An example of macroscopic traffic models is Cell Transmission Model developed by Daganzo (1994) based on the kinematic wave theory. The model represents traffic road segment divided into smaller parts known as cells and the numbers of vehicles in each cell are estimated for every time step. Recently, the MFD has been used to describe the network-wide traffic based on the Lighthill-Whitham-Richards (LWR) model. The aggregated traffic parameters, average speed, average flow and average density, characterise the network traffic (Daganzo, 2007).

Microscopic traffic models require a detailed picture of individual vehicle activities such as accelerations, deceleration, speeds and the driving behavior. This model requires very complex and detailed input data details with high level of accuracy. An example of microscopic traffic models is Car Following and Lane Changing. There are several microscopic traffic simulators and software model traffic networks at microscopic scale, such as VISSIM, AIMSUN, PARAMICS and CORSIM.

Also, there are some advanced developments that combine some of the characteristics of macroscopic models and some characteristics of microscopic models. These hybrid mesoscopic traffic models still require detailed data of individual vehicle activities, however, it can be an aggregated level to overcome the costs and time required when collecting data. Examples of mesoscopic models are headway distribution models, the cluster models and gas-kinetic models.

2.2.1 Background on Aggregated Evaluation of Traffic Network

Much attention has been given on modeling traffic behavior at both microscopically and macroscopically. Over the past forty years, considerable attention has been given to modeling the aggregate behavior of vehicles across an entire network in order to evaluate the network-wide performance. The earliest works on traffic aggregate evaluation were examined by Greenshields (1935) using the photographic method to observe the traffic flow and speed on two lane single road. From the observations, the relationship between speed, density and flow was proposed. Smeed and Wardrop (1964) studied macroscopic traffic variables using data from Central London and proposed that average network flow decreases linearly with the cube of average speed. This relationship was then used with the dimensional analysis by Smeed (1968) to derive a function relating the maximum number of vehicles that can enter central area as the fraction of the capacity of the road.

Godfrey (1969) supported the findings by Smeed (1968) and proposed a unimodal relationship between average flow and average density and between average speed and average flow in network level. The models were developed using the network structure by taking aerial photos for the road network to determine the minimum average journey speed in a town center. Thomson in 1967 studied macroscopic traffic variables in central London and found a linear-decreasing relationship between the average network speed and average traffic flow. The data had collected when the road network was not congested. Also in central London, Wardrop (1968) developed a model showing that with an increase in the number of junction per mile, the average speed decreased and he found average speed was mainly influenced by the traffic density in the network. Zahavi (1972) using real date for some cities in the United States and the United Kingdom found an inverse monotonic relationship between average speed and average density.

Although the above models may describe traffic performance accurately at free-flow conditions, they fail to recognise traffic behaviour when the network is saturated or approaching gridlock, especially when both speeds and flow are low. Therefore, more comprehensive models are required to describe traffic state accurately in a network. Herman and Prigogine (1979) developed a TFM based on traffic flow from the kinetic theory to propose the relation between average vehicle speed and the fraction of vehicles in a network that is stopped. Further investigation on the TFM have been done to describe the relation between the fractions of vehicles stopped and network density (Herman and Ardekani, 1984). They found that the fraction of stopped vehicles can be formulated by the average density of network. In addition, Mahmassani (1984) performed a series of studies on traffic evaluation for different urban cities based on the two-fluid theory.

2.2.2 Macroscopic Fundamental Diagram

Daganzo (2007) re-introduced the idea of a relation between macroscopic traffic variables (speed, flow and density) on an urban network as a part of an urban dynamic traffic model. The study showed how a traffic network could be monitored and controlled as a single reservoir without full knowledge of detailed origin-destination data that are sometimes very hard to obtain. This study was the early works on the MFD used currently, and study hypothesised that the traffic flow and congestion are distributed homogeneously in a neighborhood.

Geroliminis and Daganzo (2007) modelled the downtown area of San Francisco using simulated data with various original destinations tables. During the simulation, the model showed low-scatter diagrams of travel production against accumulation, and the space mean speed against accumulation independently from the OD demand. The real data from the city of Yokohama further proved an independently stable exit flow rate ratio against the network flow from traffic demands. The data collected from the loop detectors and GPS data from devices installed on taxies.

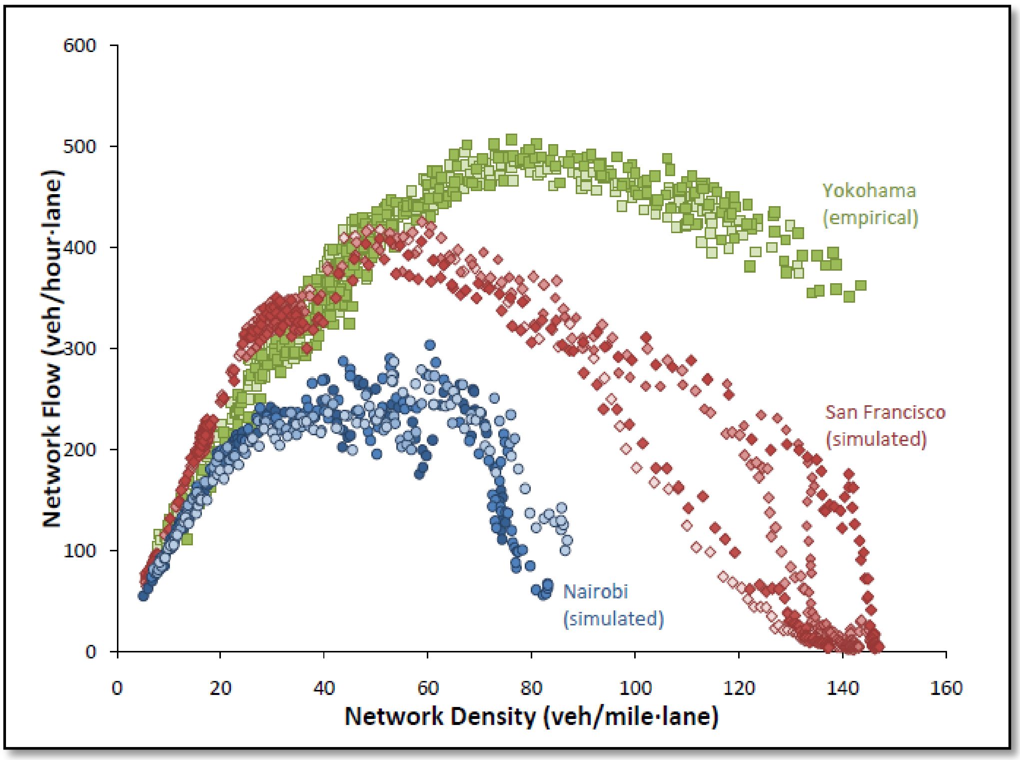


Figure 2.6: The MFDs of Yokohama, San and Nairobi

The authors were able to obtain a well-fitted MFDs describing the relations among the space mean speed, density and flow of the network (Daganzo and Geroliminis, 2008). The authors also showed analytical formulae for the MFD as a function of the roads lengths, their conventional macroscopic speed-flow model fundamental diagrams and the intersection control strategies, independently to the traffic demand. Simulations data of San Francisco, California and empirical data from Yokohama, Japan, were used to prove the existence of MFD for real traffic system (Figure 2.6). This result was also supported in a more recent study that derived the MFD of Nairobi, Kenya using simulations (Gonzales et al., 2009).

Ji et al. (2010) studied the shape of the MFD for a part of Amsterdam network using traffic simulation model. The network was a mixture of two types of roads, namely urban roads and freeways. The author found that the shape of the MFD is not only the property of the network itself such as the type of the roads and traffic demand but also influenced by traffic control measures. Moreover, the shape of the MFD is highly sensitive to rapid changes in traffic demand. Mazloumian et al. (2010) simulated artificial network to investigate the effect of inhomogeneity in spatial distribution of densities on the shape of MFD. The author found that there is an existing relationship between observed network flows and the standard deviation of roads densities across the network. In addition, spatial scatter of the network densities increases continuously over time and the highest value of network flow obtained when the spatial scatter of vehicle densities are lowest. Further investigations were done to study the impact of heterogeneity phenomena on network performance used simulated data (Daganzo et al., 2011; Knoop et al., 2011).

Geroliminis and Sun (2011a) proposed the definition of well-defined MFD in a traffic network and explored the hysteresis phenomena. They used field data gathered from loop detector from Yokohama downtown in Japan. The found that high variation of link densities during congestion state has caused a hysteresis phenomenon in traffic flow. Geroliminis and Sun (2011b) also investigated the existence of well-defined MFD on freeway network using field data from freeways in Minnesota. The results of this study supported the findings from Yokohama and emphasise that different spatial and temporal distribution of traffic in network causes hysteresis phenomena. Similar results were found by Saberi and Mahmassani (2012) when they studied the traffic in Portland city.

Most recently, Leclercq and Geroliminis (2013) investigated the effect of different routing strategies on the shape of the MFD. The study found that the shapes of MFD were significantly affected by spatial scatter of vehicle densities. Zhang et al. (2013) studied the effect of using different types of signal timing on shape MFD. They showed that changing in the signal timing will result in different shape of MFD due to the change in the spatial heterogeneity of density in network. And they suggested that the performance and capacity of network could be improved by maintaining the homogeneity of density in traffic network.

2.2.3 The Two-Fluid Model

The TFM was developed by Prigogine and Herman (1971) to model the traffic on the non-highway urban network to overcome the associated difficulty by using microscopic traffic model to evaluate the quality of service in urban traffic. The TFM is macroscopic model that describes the relation between the trip time per unit distance and the stop time per unit distance as network performance assessment. This relation can be utilised to determine the fraction of in-motion or stopped vehicles in the network, which can help measure the quality of traffic service in network-wide and assist system control. The TFM has been successfully representing the traffic conditions during congested period in various urban networks (Herman and Prigogine, 1979).

The TFM classified the vehicles' activities in the urban street into two regimes, moving and stopped vehicles as result of traffic congestion, traffic signals, stop signs, and other traffic control methods, however, not vehicles stopped due to loading and unloading of goods or parked vehicles. This model assumes that the average running speed in a street network is proportional to the fraction of vehicles that are moving and the fractional stop time of a test vehicle circulating in a network is equal to the average fraction of the vehicles stopped during the same period (Herman and Ardekani, 1984).

2.2.3.1 *Two-Fluid Model – A History*

Some empirical studies (Ardekani, 1984; Ardekani and Herman, 1987; Herman et al., 1988) have shown that the two parameters of the TFM can be used as indicators of the performance of urban street networks. On other hand, Mahmassani (1984) and Williams (1985) have shown the application of the TFMs on simple grid networks by simulation approach based on car following theory. Similarly, Denney et al. (1993) performed a calibration of TFM through a microscopic simulation model using field data collected from CBD of San Antonio, Texas. In addition, Herman and Ardekani in (1984) have presented the estimated model parameters (T_m and n) of the TFM in different cities networks around the world like Austin, Dallas, Houston, London, Melbourne, and Sydney. Recently, the TFM has been used to characterise traffic flow on Arlington networks, Texas (Vo et al., 2007).

Other studies have shown that the characteristics of the TFM are affected by the network features (Ayadh, 1986; Ardekani et al., 1992; Bhat, 1996) and driver behavior (Herman et al., 1988). Recently, Dixit et al. (2011) found that the parameters of the TFM are also influenced by the level of aggressiveness in driver behaviour likewise roadway characteristics. A significant relation was also found between the two-fluid parameters and crash rate in general, and severe crash rate as well. Dixit (2013) proposed further development of a behavioural framework to explain correlations between the TFM parameters and crash likelihood. In addition, Park and Abdel-Aty (2011) showed another application of TFM on safety by developing a model that can predict the crash rate in network using catastrophe models.

Also, another study has investigated the effect of various time of the day on the TFM parameters. Dixit (2012) showed that the driver behaviour in urban arterial networks is statistically different periods such as morning peak, midday and evening peak. In addition, Dixit have also found that the environmental factors significantly affect the TFM.

Moreover, Jones and Farhat (2004) have validated the TFM at individual urban arterials using data from two different arterials. The author has shown that the TFM is capable of describing the quality of traffic at arterial scale in addition to network scale. One of the major findings is that the TFM can be used at different levels of spatial resolution ranging from network, corridor and link levels.

2.2.3.2 *Application of TFM to Obtain the MFD*

Herman and Prigogine (1979) suggested a theoretical relationship between the fraction of the stopped time and the average density in the network. In addition to the TFM parameters T_m and n, parameter p might be useful in describing the character of a traffic network system as shown in (2.6) below. As f_s increases, the density in the network increases and when $f_s = 1$, the density equals to jam density.

$$f_s \propto \left(\frac{k}{k_m}\right)^p \tag{2.6}$$

Ardekani and Herman (1987) used time-lapse aerial photography over Austin and Dallas to determine the averages of density, speed, and a fraction of vehicles stopped and studied the relations among such network-wide variables using simulations. These relations can provide helping tools to describe the performance of traffic system in urban street networks. The data in this project have been collected in four periods, starting at 8:00 a.m., 12:00 noon, 3:30 p.m., and 5:00 p.m. and each lasting 2.5 to 3 minutes. Figure 2.7 is a theoretical chart of the fraction of vehicles stopped versus density in a network for values of p in the range 0.10 to 2.0 in 0.10 increments. The authors have found that comparing two different networks under the same f_s is not necessarily equivalent to comparing these networks under the same density (k) since the relation between f_s and k would likely be different for different networks. Thus, a functional relation between f_s and k requires more variables to describe the TFM and allow the comparison of networks under similar traffic density.

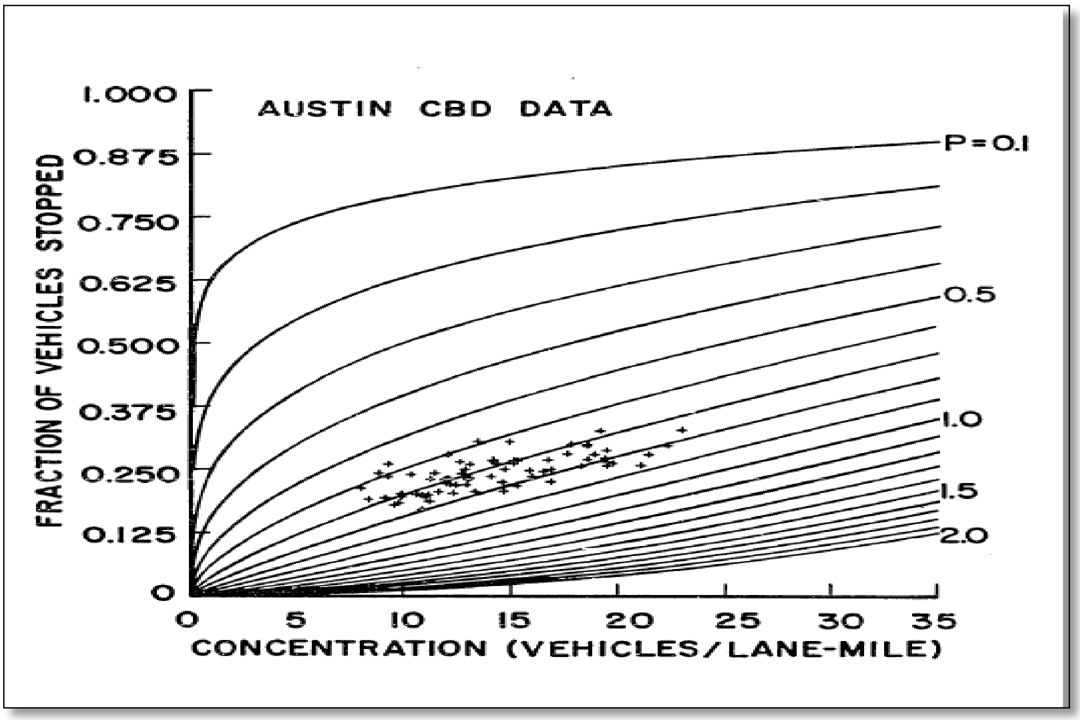


Figure 2.7: Flow vs. Density for the Fixed Values of Tm, n of the Austin CBD (Ardekani, 1984)

Recently, a new study empirically investigates the relation between MFD and TFM using GPS data from probe vehicles (Dixit and Geroliminis, 2015). In this study, the authors also attempted to investigate the effects of using different monitoring techniques on the TFM parameter estimation process using an extensive dataset of more than 20,000 probe vehicles from Shenzhen, China. It was found that the TFM using individual-level data are remarkably different from the model developed using aggregated network level data. Again, TFM developed using the average of fraction stopped by vehicles and the average of running time of vehicles in network show well fit with the aggregate level data. This paper shows that linking the MFD with TFM could raise the possibility of utilising GPS data to control traffic in networks with similar methods using the MFD. In addition, the authors have theoretically and empirically proven that with 30% of GPS data from cell phones, a reliable MFD and TFM of the network can be estimated. Likewise, Gayah and Dixit (2013) have satisfactorily estimated the average vehicle density of the network in real-time using data collected from circulating probe vehicles.

Recently, new technologies, such as image processing, GPS and smartphone applications, have been used to collect detailed traffic data over network-wide. These methods ease the instantaneous field traffic data collection at the macroscopic level and may provide more accurate estimates for traffic parameters like traffic flow, speed, mean cruising and stopping time, and so forth.

2.3 Summary

It was observed from the presented literature that a lot of work has already been undertaken to study the traffic condition in network-wide to implement effective strategies of prediction, monitoring, and regulation in order to optimally use the existing infrastructure and improvements in environmental performance. However, the availability and the cost associated with gathering data have played an important role in the emission modelling and level of approach. One of the approaches commonly used for air quality assessment in urban traffic network is macro-scale models. Using simulations data gathered from traffic models software (such VISSIM), or data empirically collected (such GPS data), the macro traffic models such MFD and TFM represent the feasible mean to understand the average behaviour vehicles in order to play a significant role in evaluating and controlling different traffic network or sub-network in an urban area. The traffic data required during evaluation traffic conditions in network can be utilised for road emission estimation. However, the link between TFM model and road emission is not discussed yet in the literature. Thus, this thesis aims to investigate the feasibly of utilising the TFM to estimate the network traffic-related emissions rate as a new application on road emissions on urban networks. The advantage of such model is that the changes in average network speed due to congestions are included in the traffic performances models.

Chapter 3.

Network Traffic Emission Model

3.1 Introduction

Most of the major cities of the world are plagued by unprecedented traffic congestion, which poses several demerits to the regional economy and environment. One of the greatest challenges faced by transport agencies is to evaluate methods for assessing the effect of traffic conditions on the emission rate on an urban road network. A variety of models exist in the literature though, which are capable of estimating emissions from vehicles at different levels of resolution along with their limitations and conditions. For example, the microscopic models provide detailed emissions estimation for small-scale networks with the limited number of links while the macroscopic models are more suitable for making large-scale network estimates. Recent technological developments in traffic models and data collection methods have facilitated and improved the ability to capture vehicle activities at a network level and provided useful tools to analyse traffic conditions.

This chapter aims to develop a new methodology to estimate the emission for traffic network at a macro-level and to address the limitations of existing approaches such as emission models based on average speed. The proposed model provides an estimate of the vehicular emission based on different modes of operation, e.g., precisely idling and cruising of vehicles. The basis of this technique is to utilise the macroscopic traffic model, known as the Two-Fluid

Model (TFM), and derive the link between vehicle stopped time (per unit distance) and vehicle cruise time (per unit distance) with emission rate. Therefore, this chapter also demonstrates a new implementation of the TFM towards emission estimation.

The TFM has been used as one of the tools to assess the quality of traffic systems in various urban traffic networks. The model represents average traffic conditions on a large-scale urban network during a given period of time (Ardekani, 1984; Prigogine and Herman, 1971). The implementation of TFM is relatively straightforward as compared to other traffic models due to the ease in collecting data required for calibration. Thus, it is suitable in the implementation of macroscopic analysis. In addition, further studies show that TFM model has been used to describe traffic flow on urban arterials and can be used to evaluate safety as well (Dixit et al., 2009; Jones and Farhat, 2004).

3.2 A New Method for Network-Wide Emission Estimation

This section comprises two main parts: Firstly, limitations of the current emission models applied at the network-wide level are discussed followed by some illustrations of their weaknesses. Secondly, the need for better methods with more/different traffic parameters for emissions measurement on a larger-scale are demonstrated with an example of an isolated case to discover the effect of the number of vehicles idling on emissions calculations.

3.2.1 Limitations of Current Emission Models

As illustrated in Chapter 2, traffic emission models have been widely used to quantify the pollution from mobile-sources at a network-wide level in order to evaluate the impact on air quality and environment. In general, vehicle emission models can be classified into two main groups; namely micro and macro level models, based on the aggregation levels of input data. This section summarises the limitation and drawbacks of the implementation of existing models at large-scale.

Currently, microscopic vehicle emission models have been proven to be a useful tool to calculate exhausts from vehicles. This is because of their ability to deal with the detailed trajectory files particularly with full dynamics (i.e., second by second) of the operating conditions of the individual vehicles. However, there are some fundamental problems related to these models especially when applied to large networks (Boulter et al., 2007; Joumard, 1999; Zachariadis and Samaras, 1997). This is because of the fact that much more data is required as an input to the model, and consequently the cost and time needed for data processing and storage. Therefore, for larger traffic networks, a microscopic vehicle emission model is not feasible and may cause undesirable result for traffic management. Although a number of studies have been conducted to rise the ability of these micro models at large-scale, however, the computational time requirements grow as the number of vehicles increases. Therefore, these types of models are mainly suitable for detailed studies, and many authors prefer macroscopic models over microscopic models to overcome these complications.

The macroscopic emission models, on the other hand, are often used to evaluate traffic emissions in large-scale networks because of their lesser data requirements. Since the traffic data used is actually aggregated, most of current models have used average link speeds to compute vehicle emissions in order to simplify the calculations. However, a number of studies have shown the existence of a significant degree of uncertainty in estimating emission rates using the current macroscopic emissions models. Furthermore, the use of average speed in traffic network as a single explanatory variable is insufficient to compute emission levels. Thus, they may result in overestimation or underestimation subjected to the cruising speed range and other traffic factors (Panis et al., 2006). Additionally, with increasing number of vehicles entering into the traffic network, the average speed in the network drops significantly due to traffic congestion. Furthermore, the spatial inhomogeneity of the traffic density due to unevenly distributed congestion results in increased variation in the vehicle speed (standard deviation of speed) because some parts of the network may be congested earlier than the other parts. Thus, the average speed in a network proves to be the only average measurement to express the traffic conditions in the network. Therefore, there is a need to quantify the effects of different or additional traffic-related explanatory variables in order to develop a model to estimate the emission rates and emission factors of vehicle in a large-scale transportation network.

3.2.2 Effect of the Number of Vehicles Idling on Emission Calculation

This sub-section investigates the impact of vehicle idling in the network on emissions calculations using a simple example. Five different scenarios of traffic conditions are created, where the average speed of vehicles traveling in the network is similar for all the scenarios (see Table 3.1 for details). In each scenario, artificial trajectories for 10 cars have been generated with the assumption of number of vehicles stopping and speed of cruising cars. An emissions simulator "EnViVer", which is software based on the microscopic emissions model VERSIT+, has been used to calculate exhaust gas emissions for each scenario (Eijk and Ligterink, 2014).

The assumptions for this test are as follows:

- During each time step, vehicles on roads are either completely stopped or moving at a constant speed.

- The stopped vehicles are due to traffic control not due to parking.
- The acceleration and deceleration effect has been excluded in this example. In other words, the trajectory of each cursing vehicle is a straight line.
- All scenarios have the same aggregate average speed, i.e., 15 km/h.
- Time step for all the scenarios is equal to 1200 sec.

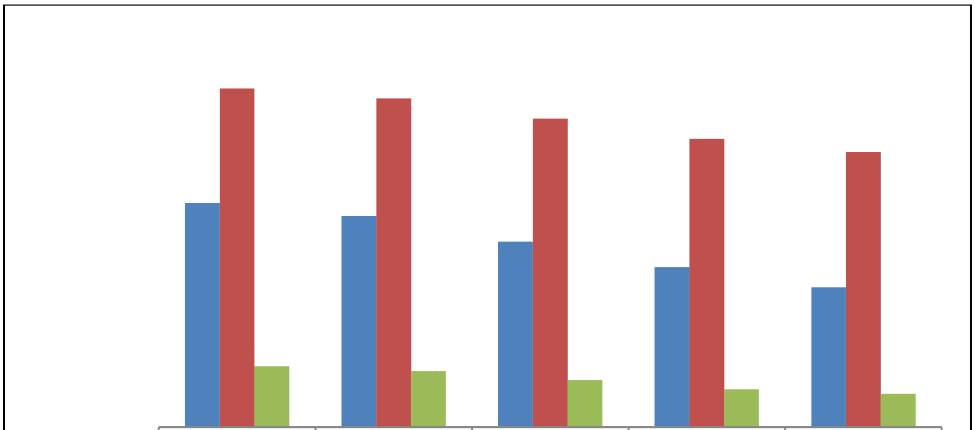
Table 3.1 shows 5 different scenarios of cruising vehicle percentage with the same network average speed (i.e., 15 km/h). For the first scenario, the fraction of cruising cars is 100%, which means no stopping cars in this case and each car is traveling at the same speed of 15 km/h. On the other hand, in scenario 5, 70% of the cars are completely stopped and the speed of cruising cars is 50 km/h, which maintains the above assumption that the network average speed should be equal to 15 km/h. In this proposed test, the difference between the five scenarios is the cruise-speed level and the average duration of idling for all the cars.

Table 3.1 Cruising vehicle percentage: different scenarios with the same network average speed.

Scenario No.	Percentage of cruising cars in network	Average Speed in network (km/h)	Speed of cruising cars (km/h)	Average duration of idling (sec/km)
1	100	15	15	0
2	90	15	16.7	24
3	70	15	21.4	72
4	50	15	30	120
5	30	15	50	192

Figure 3.1 shows the variation of total emissions for different scenarios. Although the network average speed is fixed in all the suggested scenarios,

different scenarios produce various quantities of total emissions of carbon dioxide (CO_2), nitrogen oxides (NO_x) and particulate matter (PM). This indicates that the emission estimations are more sensitive to the cruise-speed levels and average idling time than the average speed of vehicles in the network.



	1	2	3	4	5
CO2_kg	14	13	12	10	9
Nox_g	22	21	20	18	17
PM_g	3.9	3.6	3.0	2.4	2.1

Figure 3.1: Variation of emissions for various scenarios with the same network average speed.

Table 3.2 shows the total emissions of CO_2, NO_x and PM between all the scenarios. For instance, when comparing the 1st and 5th scenarios, we find that the difference in the amount of total emissions is 38%, 19% and 45% for CO_2, NO_x and PM respectively. Similarly, when 10% of cars are stopped in the case of 2nd scenario, a 6% decrease in the amount CO_2, 3% decrease in NO_2 and 8% decrease in PM can be seen in contrast to the 1st scenario where all cars are cruising. Additionally, the results indicate that the emissions factor for CO_2 varies from 178 kg/km to 285 kg/km and is a function of the average idling time of vehicles in a network.

Table 3.2: Variation of total emissions and emissions factors for various scenarios with the same value of network average speed.

Scenario No.	Total Emissions			Emissions Factors		
	CO_2 (kg)	NO_X (g)	PM_{10} (g)	CO_2 (kg/km)	NO_X (g/km)	PM_{10} (g/km)
1	14	22	3.9	285	431	77
2	13	21	3.6	269	418	71
3	12	20	3.0	236	393	60
4	10	18	2.4	203	367	48
5	9	17	2.1	178	350	42
Average of all Scenarios	12	20	3.0	234	392	60

The results from this test clearly show the significance of considering the traffic condition of a network in order to improve the emission assessment at a network-wide level. The conventional macroscopic emission models, that use the average speed of vehicles traveling in the network, are not reliable since different traffic conditions in a network can yield similar average speeds. This analysis evaluates the impact of number of stopped vehicles only; therefore there are other traffic related parameters such as acceleration and deceleration, which have an impact on emission rates too for same distance travelled.

In conclusion, it is justified that more network-level traffic parameters should be considered in order to improve the conventional approach of estimating emission at a macro-level using average speed only. The average speed of a traffic network alone is not sufficient to provide enough representation of the driving pattern as well as the traffic condition. This raises the need to find more efficient methods to estimate the emissions. Taking into account the average cruising time and average idling time of vehicles traveling in network as the new parameters may improve the emission prediction from vehicles under different traffic conditions.

3.3 Emissions Models Development Approach

This section contains two main parts: Firstly, TDM has been used to estimate the proportion of the time spent in cruising and idling modes in order to simplify the estimation of traffic parameters in an urban network. Secondly, the analytical approach with the new input traffic variables is proposed in order to investigate the linkage between the cruising and idling times with the associated emission rate.

3.3.1 Traffic Parameter Calculations

As discussed earlier in Chapter 2, the TFMs have been developed from kinetic theory of traffic flow to establish the analytical relations of macroscopic traffic parameters in large cities, which assumed that the whole traffic stream in urban street network can be divided into two components, either vehicles are moving or vehicles are stopped as a result of traffic jam, traffic signals, stop signs, and other traffic control method, but not for parking since they have been treated as not part of traffic stream (Herman and Prigogine, 1979).

According to the TFM, the average speed of moving vehicles is expressed as a product of the fraction of vehicles that are moving, f_r and the average running speed of moving vehicles, V_r.

Mathematically:

$$V = V_r \, . \, f_r \tag{3.7}$$

where the average running speed of moving vehicles V_r is a function of the fraction of moving vehicles to the n^{th} power, and the maximum free-flow speed V_m when no vehicles are stopped ($f_s = 0$).

$$V_r = V_m \, . \, f_r^n \tag{3.8}$$

where n is one of the TFM parameters that represents the quality of traffic service in a network. Substituting in (3.8) in (3.7), we get

$$V = V_m \cdot f_r^{(n+1)} \tag{3.9}$$

$$V = V_m \cdot (1 - f_s)^{(n+1)} \tag{3.10}$$

The boundary conditions are satisfied for above equations; so when there are no stopped vehicles (i.e., all vehicles are moving), the fraction of moving vehicles f_r is equal to 1, therefore, the average running speed of moving vehicles V_r is equal to average maximum speed V_m.

Note that:

$$\mathrm{f_r} + \mathrm{f_s} = 1 \tag{3.11}$$

$$\mathrm{T_m} = 1/V_m \tag{3.12}$$

$$\mathrm{T_r} = 1/V_r \tag{3.13}$$

$$\mathrm{T} = 1/V \tag{3.14}$$

where T_m is the average minimum free flow travel time per unit distance travelled, T_r is the average time spent running per unit distance travelled and T is the average trip time per unit distance.

In TFMs, it is assumed that in homogenous traffic system, over same period, the fraction of the number of vehicles that are moving to the total number of vehicles is equal to the fraction of average running time per unit distance T_r to the average trip time per unit distance T, which is known as the ergodic assumption (Ardekani, 1984; Herman and Prigogine, 1979; Williams et al., 1985b). It is expressed as follows:

$$f_r = \frac{T_r}{T} \tag{3.15}$$

This assumption holds as long as the traffic density does not rapidly vary during the time of observation. Data from two different cities in the USA, Austin and Dallas, show that for a specific network under similar level of concentration has a similar ratio of moving vehicles (Ardekani and Herman, 1987). The study also indicated that the average fraction of vehicles stopped during a time period is a function of the average density in the network during that time.

Substituting (3.15) in (3.8), the TFM can be translated into the relationship between the total time spent cruising per unit distance travelled and the average travel time per unit distance as shown in (3.16):

$$\mathrm{T_r} = T_m^{1/(n+1)}\ T^{n/(n+1)} \tag{3.16}$$

So, T_s can be written as:

$$\mathrm{T_s} = \mathrm{T} - T_m^{1/(n+1)}\ T^{n/(n+1)} \tag{3.17}$$

Note that all the variables used in the TFM illustrate average quantities of all vehicles over the entire traffic network (Mahmassani et al., 1987; Williams et al., 1987).

The quality of traffic service of an urban network can be characterised by the values of TFM parameters(T_m and n). The parameter T_m corresponds to the minimum trip time per unit distance in a given network when there are no stops. Therefore, it represents the average running time when the network demand is nearly zero (Williams et al., 1995). However, this parameter cannot be measured directly, since traffic data from urban network always shows a level of congestion even when the density is near zero because of the impact of traffic control such as signals and network features. A high value of T_m indicates lower network performance with low free flow speed due to poor road geometry and/or poor signal timing. The typical range of $T_m$is from 55 sec/km (V_m=65 km/h) to 115 sec/km (V_m=32 km/h).

On the other hand, the parameter n represents the degree of sensitivity of travel time change in a particular network to the fraction of stopped vehicles or to the congestion level due to increased demand. According to earlier studies, n always has a positive value, between 0.8 and 3.0, and a lower value means a better capacity against the increase in demand.

In order to obtain the parameters of the TFM, a log (base 10) transformation can be applied to both sides of the (3.16), followed by a simple least-square regression on the transformed equation. It is expressed as follows:

$$\log T_r = \left(\frac{1}{n+1}\right) \log T_m + \left(\frac{n}{n+1}\right) \log T \tag{3.18}$$

which can be written as:

$$\log T_r = A + B \log T \tag{3.19}$$

where

$$\mathrm{n} = \left(\frac{B}{1-B}\right) \tag{3.20}$$

$$T_m = 10^{\left(\frac{A}{1-B}\right)} \tag{3.21}$$

Thus, (3.19) provides a linear relationship between T and T_r, while A and B are the intercept and slope of the log transformation of T respectively.

3.4 Model Development

In order to address the limitations of the conventional average speed model, it is hypothesised that the emissions should be calculated using the additional explanatory variables as they provide a better reflection of the average vehicle activates on a network-wide level since the average speed does not contain enough information for environmental assessment. There are many traffic-related factors that have an impact on the amount of exhaust emission such as acceleration, deceleration, cruising speed, time of idling and the number of stops. However, taking all these factors as input variables in a large-scale model is challenging because of the complexity of data collection, data storage and computations, especially in dynamic assessment. Since we are not interested in a detailed behaviour of traffic on the network, thus all traffic-related factors are not included, and in order to minimise the variation of vehicles average speed due to vehicles stopping, the emission should be calculated during cruising and idling mode separately. In this section, a new analytical model is developed in order to provide emissions evaluation of the network-wide level based on macroscopic traffic parameters. Using these assumptions, the basic formula can be derived as follows:

$$\mathrm{E_f} = f(T_r, T_s) \tag{3.22}$$

$$\mathrm{E_f} = \mathrm{e_r T_r} + \mathrm{e_s T_s} \tag{3.23}$$

Where, E_f is the emission factor, which denotes the emissions for the total vehicle-kilometres travelled in the network and can be expressed as a unit of pollutant per unit distance travelled, e_r is the emission rate corresponding to the cruising mode and denotes emissions for the total vehicle-time moving in the network and expressed as a unit of pollutant per unit of time moving. Finally, e_s is the emission rate from vehicles at idling mode, which indicates the amount of emissions for the total time stopped in the network and can be expressed as a unit of pollutant per stopped time.

Equations (3.16) and (3.17) can be used to integrate the emission rate and traffic variables from TFM and to develop the emission factors as a function of T, T_m and n. The emission factor can be written as follows:

$$\mathrm{E_f} = e_r\left(T_m^{1/(n+1)}\ T^{n/(n+1)}\right) + e_s\left(\mathrm{T} - T_m^{1/(n+1)}\ T^{n/(n+1)}\right) \tag{3.24}$$

The (3.24) is a new methodology for estimating the emission for traffic network at a macro-level. Re-writing (18), we get:

$$\mathrm{E_f} = e_r\left(T_m^{1/(n+1)}\ T^{n/(n+1)}\right) + e_s\,\mathrm{T} - e_s\left(T_m^{1/(n+1)}\ T^{n/(n+1)}\right) \tag{3.25}$$

The final equation for the model can be written as follows:

$$\mathrm{E_f} = (e_r - e_s)\left(T_m^{1/(n+1)}\ T^{n/(n+1)}\right) + e_s\,\mathrm{T} \tag{3.26}$$

where,

E_f : Emission factor (grams / km distance travlled)

e_r : Cruising emissions rate (grams / sec of cruising)

e_s : Idling emissions rate (grams/sec of idling)

T : Trip time per unit distance(h / km)

n : An indicator of the quality of traffic service in the network

T_m : Average minimum trip time per unit distance

T_r : Total time spent cruising per unit distance traveld (h / km)

T_s : Total time spent idling per unit distance traveld (h / km)

Although (3.26) uses a single traffic variable T as the main input, by using the network parameters $T_m$and n, the model is able to quantify the ratio of average time of vehicles moving to stopping and this is one of main advantages of using the TFM. Therefore, the effect of different modes of vehicles under various traffic conditions is considered in the proposed emissions models.

3.5 Emission Rate Calculations

3.5.1 Emission Related to Idling Mode

In urban street networks, vehicles generally come to a stop due to traffic conditions and traffic control such as congestion, traffic signals or stop signs. The term 'idling time' is different from the 'average delay time', which has been used widely in various traffic models. Idling time implies the situation when the speed and the travelled distance of the vehicle approaches zero.

The excess emission during idling mode depends on the vehicle-related factors, namely the engine size and the engine fuel type, but not traffic-related factors. However, the impact of vehicle characteristics and manufacturing technology with regards to idling emission rate is considered as the vehicles fleet compositions factors. Thus, the variance sample time of a day is significantly affecting the emission rate of stopped vehicles. For instance, the emission rate whilst idling is considerably higher during rush-hour periods in early-morning due to increase in the heavy-duty vehicle ratio (Grieshop et al., 2006). Additionally, for specific vehicle fleet compositions, the idling emission rate (g/h) for different exhaust gases (CO_2 and NO_x) and PM are assumed constant. On the other hand, this research attempts to address the limitations of the average speed model w.r.t traffic conditions, travel-related factors and all other non-traffic factors are generally held fixed.

The idling emissions rate is estimated separately for different classes of vehicles; for example, light duty cars have different rates than heavy-duty vehicles in city use. Table 3 shows the typical values of emission rate per hour of CO_2, NO_x and PM_{10} for each vehicle category. These values are further used in the microscopic emissions model VERSIT+ (Envier software).

Table 3.3: Idling emissions for various pollutant types from different vehicle classes.

	CO_2 (g/h)	NO_X (g/h)	PM_{10} (g/h)
Light Duty City	**575.00**	**2.43**	**0.158**
Medium Duty City	**4854.42**	**56.86**	**1.41**
Heavy Duty City	**7144.96**	**58.87**	**1.66**
Bus in City	**8423.14**	**55.97**	**1.85**

Table 3.3 shows that each pollutant has different idling emissions rates among various vehicle categories. For instance, on comparing the light duty city class with the heavy duty city class, we find that the difference in the amount of

idling emission rates are 91%, 96% and 91% for CO_2, NO_x and PM respectively. This is because of the impact of vehicle characteristics and manufacturing technology such as the engine size and the engine fuel type, which we term as the vehicle-related factors.

3.5.2 Emission Related to Running Mode

The objective of this subsection is to quantify the impact of vehicle cruising mode on vehicle emission rates. Two different standards, Federal Test Procedure (FTP), drive cycles sets are used to drive the emissions rates of vehicles associated with running mode. Driving cycle is a set of second by second data of average vehicle speed representing the average performance of the vehicle while traveling on roads. The FTP drive cycles include the FTP-72 cycle which is also called "the city test cycle" and the EPA New York City cycle. Each of these cycles has been created by the Environmental Protection Agency (EPA) in the United States to represent urban driving behaviour to measure tailpipe emissions and fuel consumption of passenger cars. As was the case in the above subsection, the VERSIT+ through the Envier software is used to measure the emissions associated with the running mode of vehicles.

The FTP-72 cycle was developed by a series of tests to simulate the performance of engine to represent city driving conditions for typical home to work trips in Los Angeles in the United States. Recently, this cycle is called the Urban Dynamometer Driving Schedule (UUDS). However, since 1972 the FTP city drive cycle has been used as a reference point for emission certification of light-duty vehicles (LDVs) in the United States. The cycle represents 1369 seconds of vehicle operating in urban roads for 12 km distance travelled. The average speed for the entire cycle is 31.6 km/h, where the maximum speed is 91.15 km/h as illustrated in Figure 3.2.

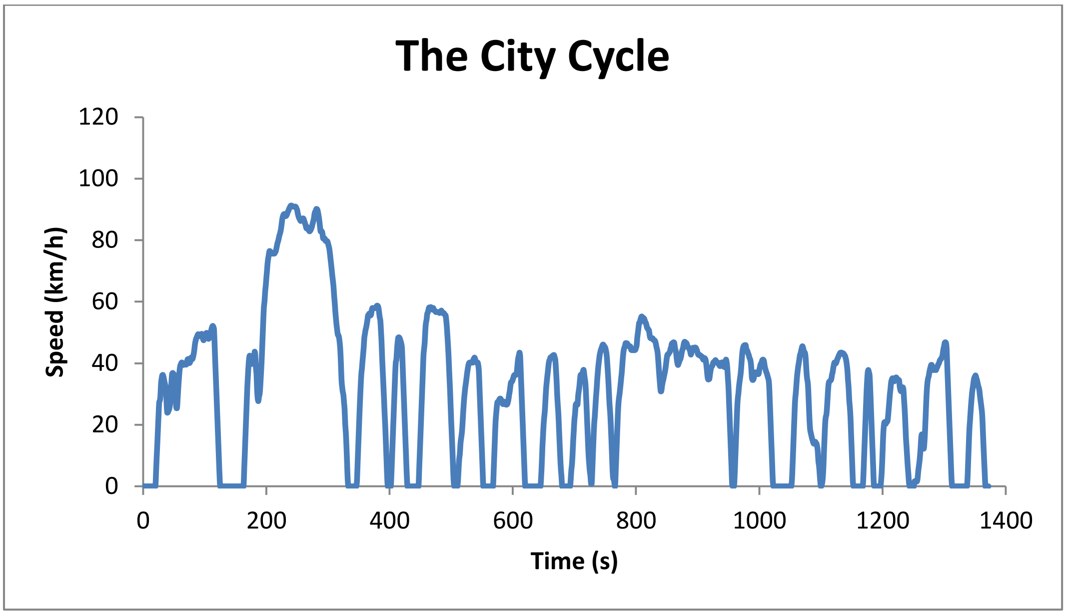


Figure 3.2: City Driving Cycle

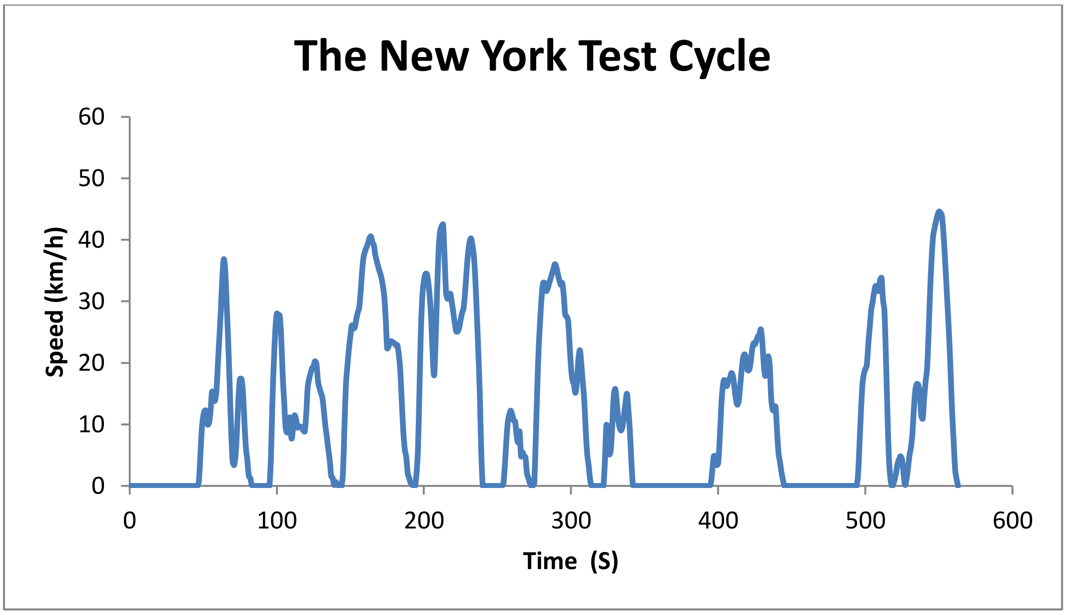


Figure 3.3: The New York City cycle

On the other hand, the New York City Cycle (NYCC) was developed in the 1970's by The Environmental Protection Agency in order to simulate mid-town Manhattan roads in New York City during heavy congestion. This test cycle is representative of the low speed stop-and-go traffic conditions. The average speed for this cycle is 11.5 km/h during 598 seconds simulated data for 1.9 km distance travelled, where the maximum speed is 44.45 km/h as illustrated in Figure 3.3.

The exhaust emission during cruising mode depends on both vehicle-related factors and traffic-related factors. However, this research attempts to address the limitation of the average speed model with respect to traffic conditions as travel-related factors and all other non-traffic factors are held fixed including the vehicle fleet composition, thus the light duty city class has been selected for emissions evaluation.

Table3.4: Summary of idling and running emissions rate for various pollutant types from of light-duty vehicles class

	Pollutant	E_{total} (g)	e_r (g/h)	e_s (g/h)
City Test Cycle	***CO2***	761	8444	575
	NO2	1.29	13.08	2.43
	PM	0.135	1.45	0.158
New York City Cycle	***CO2***	2657	8838	575
	NO2	4.36	14.07	2.43
	PM	0.52	1.72	0.16
Average	***CO2***	1709	8640	575
	NO2	2.82	13.58	2.43
	PM	0.33	1.59	0.16

Table 3.4 illustrates the running emissions rate per hour ofCO_2, NO_x and PM_{10} for light-duty vehicles (LDVs) class. These values are calculated using the microscopic emissions model VERSIT+ (Envier software). Although both UUDS cycle and NYCC cycles are different with many factors affecting the total quantity of emission (e.g., average speed, percentage of time idling, number of stops as well as average acceleration and deceleration), there are no significant

differences in the amount of emission per time. For instance, by comparing the emission rate of CO_2 of these cycles, we find that the difference is 0.057%, similarly the differences in the emission rates are 0.07% and 0.157% for NOx and PM respectively. Therefore, the average result from these two driving cycles can be applied to calculate various vehicular emissions. Thus, it is concluded that the proposed model is capable of estimating emission factors for each driving mode on a network level.

3.6 Summary

In this Chapter, the limitations of the existing models in emissions evaluation for a large urban network particularly with greater number of vehicles are described. A novel model is proposed to estimate the vehicular emission in the traffic network by taking into account the impact of various vehicle operation modes, precisely idling and cruising. The macroscopic traffic model, which is also known as the Two-Fluid Model (TFM), has been used to estimate the fraction of vehicles that are stopped in an urban network. One of the main advantages of using the TFM is its ability of analysing the traffic conditions using one of the sample techniques such as such prop vehicle representing entire network. Such models can serve as an effective tool to facilitate the evaluation of the effect of traffic conditions and air quality assessment in traffic management and real-time monitoring.

Chapter 4.

Application of Proposed Model in Orlando Network

In this Chapter, the proposed model is tested and validated using the traffic micro-simulation data from VISSIM and emissions micro-simulation data from EnViVer, which are obtained for Orlando downtown network. A new methodology is presented based on detailed emission evaluation to evaluate the road traffic emission factors and to verify suitability of the proposed model for large-scale networks.

Initially, the TFM calibration is performed in order to calculate the value of T_m and n of Orlando downtown network followed by an analytical approach to estimate the macroscopic fundamental diagram model (MFD) for Orlando downtown network using conventional macroscopic speed-flow models and TFM. Then, the proposed model is applied to estimate the carbon dioxide emission rate associated with the average vehicles activities in traffic network. Finally, a relationship between vehicles emission and network traffic parameters is investigated to discover the impact of increasing urban network density on total emissions rate (E_{total}) and average emissions factor (E_f), and these results are compared with analytical modelling simulation results.

4.1 Study Area

The study area of this Chapter comes from Orlando downtown in United States. This simulated traffic network was developed in the VISSIM micro-simulation software to be used for one of the Florida Department of Transportation projects (Dixit et al., 2009). The simulated network represents part of the Orlando downtown which includes the surface streets and excludes the two freeways as presented in Figure 4.1. The traffic data was collected from the City of Orlando which contains about 107 signalised intersections over area around 2.7 x 2.7 km. Generally, speed limit in Orlando Downtown Streets was below 60km/h. The simulation represents 3 hours of a.m. and p.m. peak period. The geometric design of roads in the traffic network such road grade are not considered. In other words, vehicles emission rates due to the upgrade and downgrades effect has not been covered in this study. A more detailed description of this simulated network can be found in Dixit (2009) and Dixit et al. (2011).

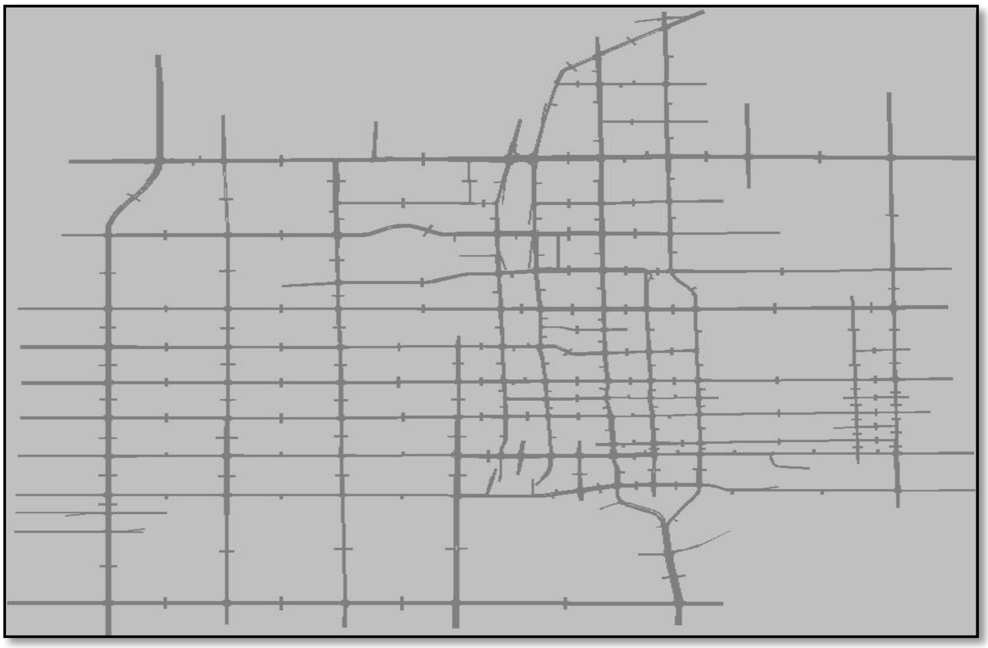


Figure 4.1: VISSIM map of downtown Orlando

4.2 Data collection:

The traffic data was obtained from the City of Orlando by mobile chase cars. Travel times and stop times for chase car was collected during peak time from 7:30 to 9:00 AM and peak time from 5:00 to 6:30 PM. These data were collected for two-fluid modelling to represent each traffic peak. Three different working days (19th to 21st February, 2008) were considered in the data collection in order to ensure that the models reflected the average operating conditions on the network.

Two techniques were used during data collection: distance-based and time-based method. In the first technique, travel times and stop times was collected from chase car while traversing one mile. This technique is also called one-mile method. The chase car's trip odometer was used to determine when a mile had been travelled. Two stop watches were required to measure the travel time and stopped time during that mile.

In the second technique, the traffic data was collected every two minutes. Similarly, this method required one stop watch to measure two minute intervals while the other stopwatch used to measure stopped time. Also, the trip odometer readings are recorded for the beginning and the end of the two minutes.

Both technologies collect the same type of data including the odometer readings, the absolute times from the stopwatch and the number of stops for the duration of each trip. The data collection process required a driver, data collector and two stop watches per chase car. More detailed information of data collection and network building of this simulated network can be found in Dixit (2009) and Dixit et al. (2011).

4.3 Calibration and Validation

The Orlando simulation network was calibrated to reflect the real-world data obtained by mobile chase cars to the simulated world. Tow of driving behaviour parameters within the VISSIM simulator was selected that can be modified to adjust a simulation. These parameters located under the vehicle following category. The two parameters were the average standstill distance and the look-ahead distance for the car following model.

The two-fluid model has been used for calibration. A trial and error method were used to match the two-fluid model generated in VISSIM with the two-fluid model computed from the field data. The process repeated until the two models were statistically similar.

VISSIM network also validated using different field data set. The validation prosses shown that the two-fluid models from the new field data and VISSIM data are statistically similar. Therefore, the simulation VISSIM network could be used to measure network performance for different scenarios. Full details on the calibration and validation procedure can be found in Dixit et al (2009 & 2011).

4.4 The Proposed Methodology

The micro-simulation model, VISSIM, is used to study the relation between vehicles emission and traffic flow parameters at a network level. The Orlando downtown network traffic is simulated in VISSIM software for 90 minutes of the peak hour. The outcomes of simulation experiments using VISSIM are vehicles trajectory files recorded for every simulation second. In order to obtain the network traffic performance, the vehicles trajectory data are aggregated to five-minute time intervals. The aggregation process is computed for whole network to calculate the average network density, flow and speed in pursuit of generating network-wide MFD. In addition, the distance travelled and time spent on each mode (i.e., cruising and idling) of all vehicles are aggregated for every 300 sconed of simulation time for entire TFM calibration.

The emissions model EnViVer, which is based on the VERSIT+, is used to estimate the traffic emissions based on second by second vehicle trajectories output from PTV VISSIM software. Since this study aimed to investigate the effect of traffic-related factors on emissions rate we are not including all vehicles class and we assumed that all the vehicles during simulation belong to the same vehicle class. Passenger cars are chosen and represented as light-duty-city-2013 in the emissions model EnViVer. The results of emissions model are also aggregated best five-minute intervals to be associated with the result of TFM and MFD of the network.

The output from the micro-simulation model VISSIM as well as the emissions model EnViVer are very large data sets, thus MATLAB software is used to facilities the analysis process. The methods of calculating MFD parameters and emissions using simulated data are presented in this section.

4.4.1 *Vehicle Trajectories Formulae of MFD*

The parameters of the macroscopic fundamental diagram model (MFD) can be obtained by applying Edie's definitions (Edie, 1963) on vehicle trajectories data. For each time period of the analysis, the average vehicle speed (V), the average flow (Q) and the average density (K) in network can be calculated as follows:

$$K = \frac{\sum_{i}^{n} t_i}{L\,\tau} \tag{4.27}$$

$$Q = \frac{\sum_{i}^{n} d_i}{L\,\tau} \tag{4.28}$$

$$V = \frac{\sum_{i}^{n} d_i}{\sum_{i}^{n} t_i} \tag{4.29}$$

where

d_i : travel distance of vehicle i

t_i: travel time of vehicle i

n : total number of vehicles that use the network during the time interval

L : total network length

τ : time interval

According to a comparison by Leclercq et al. (2014), the Edie's method to estimate the MFD is the most accurate methods among others such as loop method, and probe method and analytical method, since it deals with the full information of vehicle trajectories over the network. This method is applicable only on data obtained from simulation software, and cannot be used on real world data since it is impossible to record each single vehicle activities.

4.4.2 Emission Calculations

Emissions are computed in every simulated-sconed for the traffic profile from PTV VISSIM software using the emissions model EnViVer, which is based on the VERSIT+. Then the output from emissions model are aggregated for every 5-minute for 90 minutes corresponding to peak hours. The average emission factor of pollutants CO_2 is calculated for each time step from all vehicles in Orlando downtown network. Then, the total emission rate of CO_2 is estimated using traffic mean flow of the Orlando network.

4.4.2.1 *Average Emission Factor*

Average emission factor denotes emissions for total vehicle-kilometres travelled in the network. It is a unit of pollutant per unit of distance travelled. In this study, our proposed model in Chapter 3 is used to compute the emission factor of CO_2. The model estimates the aggregated emission rate from various vehicle operation modes, i.e., idling and cruising. The values of the emission parameters in as given in Chapter 3 associated with CO_2 are used corresponding to passenger cars while T_m and n in the proposed model are obtained from TFM calibrations. The proposed model (4.30) estimates emission factor for each time interval (τ) by network-based average time by vehicles spent in cruising and idling mode. It is expressed as follows:

$$\mathrm{E_f}(\tau) = (e_r - e_s)\left(T_m^{1/(n+1)}\ T(\tau)^{n/(n+1)}\right) + e_s\,\mathrm{T}(\tau) \tag{4.30}$$

Where, E_f denotes average emission factor for whole traffic in network, e_r *and* e_s are cruising and idling emissions rate respectively, τ is the time interval of temporal aggregation (5 min), T is the average trip time per unit of distance travelled, which is equal to the total distance travelled by all vehicles during the time interval (τ) divided by total time spent by all vehicles in the network.

4.4.2.2 *Network Total Emission*

Network total emission denotes the total emissions discharged from vehicles in each time-step. It represents the total amount of air pollutants released by a specific traffic network during a specific time period. It is an essential tool to estimate the contributions of traffic-related emissions into total national emissions. The total emissions for specific traffic network can be obtained from total distance travelled by vehicles during given time period (see Smit et al. (2010) and Yao et al. (2011)). The total emissions in network are calculated as follows:

$$\mathrm{E_{total}}(\tau) = E_f\,(\tau) \times VKT(\tau) \tag{4.31}$$

Where,

E_{total} $= total\ emission\ from$ all $vehicals\ i\ in\ time\ interval\ \tau$

E_f = average emission factor $from$ all $vehicals\ \ in\ time\ interval\ \tau$

$VKT\ (\tau) =\ total\ distance\ travelld\ on\ a\ network\ in\ time\ interval\ \tau$

Assuming that the traffic density in a network is spatially homogeneous, the VKT can be computed using Edie's equation (4.28). So, the total emission for a specific traffic network can be estimated using average network flow during given time period (τ) and the total network length (L). The VKT on traffic network is given as:

$$VKT(\tau) = Q(\tau) \times L \times\ \tau \tag{4.32}$$

From (4.31) and (4.32), we can conclude that the network total emission is function of the average traffic flow over a given time period. The final mathematical model for the network total emission can be written as:

$$\mathrm{E_{total}}(\tau) = \left[E_f\,(\tau) \times Q(\tau)\right] * (L \times \tau\,) \tag{4.33}$$

Where L and τ is the spatial and temporal analysis windows size respectively. The model (4.33) presents mathematically the relation between network total emission and average emission factor in network-wide. The E_{total} is obtained using the macroscopic traffic flow of network. The model input variables E_f and Q are function of macroscopic traffic performance in network. Therefore, the above model estimates the emissions in the network without dealing with a detailed data representation for each vehicle's activities.

4.5 Data Analysis and Results

Following sequential steps are required to reach to a final conclusion:

1. TFM calibration is performed to calculate the value of $T_m$and n of Orlando downtown network using simulated data from VISSIM software.
2. Analytical estimation of MFD for Orlando downtown network using the conventional macroscopic speed-flow models have been used widely on a single street level, then comparing the result with MFD computed using TFM.
3. The CO_2 emission factor and network total emission are computed using proposed model, then relations between the MFD parameters (flow, density and speed) of Orlando network with corresponding macro emission variables (E_f and E_{total}) are determined.

4.5.1 Two-Fluid Model Calibration

As mentioned earlier, Orlando downtown network was performed in a microscopic simulation VISSIM for 90 minutes. The vehicle trajectory data has been aggregated over the 5-minute interval and is used to determine the TFMs parameters (T_m and n). The aggregated traffic data were from all vehicles over the entire network. The data from VISSIM were used to calculate the travel time, running time, and stopped time, all expressed in sec/km. For the purpose of the TFM calibration, traffic information like average trip time per unit of distance (T) and average time spent running per unit of distance T_r are only required. The logs of travel time [$log\ (T)$] and running time [log (T_r)] were calculated and then applied to the regression equations as discussed in Chapter 3. Linear regression is used in order to obtain A and B. Then, these values were used in (3.30) and (3.31) to calculate the two-fluid-model parameters T_m and n.

The final computed values of the estimated TFM parameters for Orlando downtown network are T_m=76.71 sec/km and *n=0.582* with R-square equal to 0.950. The value of R-square result from linear regression models is indicating that the TFM provides a good fit to simulated data obtained from VISSIM for Orlando downtown network.

Figure 4.2 shows a plot of log(T) vs. log (T_r) and can be used to perform a visual comparison of traffic data from different methods of calculation, estimated analytically from two fluid model and simulated using microscopic traffic models VISSIM. In general, we can say that the value of T_r estimated from two fluid models under-saturated, saturated and over-saturated traffic conditions is within the range of simulated data gathered from VISSIM. However, there is a discrepancy between the results of the analytical model and from simulations especially at higher travel times. This indicates that TFM cannot be used to evaluate the Orlando downtown network performance under very high-congested traffic conditions since the TFM cannot represent the actual traffic condition.

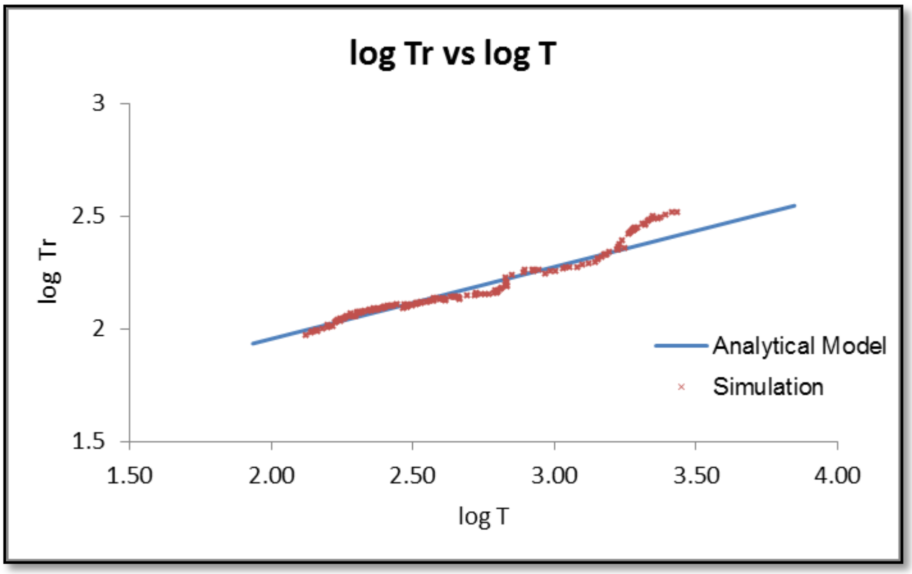


Figure 4.2: The trip time vs. the running time – a comparison between estimated from TFM and the simulated results

4.5.2 *Analytical Estimation of MFD for Orlando Downtown Network*

This section is classified into sections sub-sections to estimate the MFD for Orlando downtown based on simulated data from VISSIM: the first part of this section represents the calibrated results from conventional macroscopic speed-flow models, which have been used widely on single street level. This result is used to determine the accuracy and consistency of such models in order to estimate network-wide traffic parameters. Second part presents the theoretical relationship between network densities and average fractions of vehicles stopped in network. The relation is utilised to compute the MFD of Orlando downtown network using TFM. Then, compare it with the best-fit model of conventional macroscopic speed-flow models.

4.5.2.1 *Conventional Macroscopic Speed-Flow Models*

Although the conventional macroscopic speed-flow models have been widely used on single street level, it is not still clear what is the best-fit mode for network-wide. This approach aims to identify and calibrate the conventional macroscopic speed-flow models for Orlando downtown network, and to identify better estimation and/or fit of the relation between average density and average speed in a network. The Orlando downtown simulation data from VISSIM are used to calibrate the above mentioned macroscopic traffic flow models. The calibration process is completed based on a five-minute temporal aggregation on network traffic parameters (flow, density and speed).

In this study, nine classical speed-density-flow macroscopic models are calibrated to characterize the network flow conditions (for more detail see appendix A). Table 4.1 shows the model names and mathematical definitions of each model; more information about such models is presented in Appendix A. In additions, table 4.1 summarises and shows the estimated traffic parameters such as free flow jam density, maximum flow with associated speed and density and the goodness of fit R-value. The descriptive analysis of the simulated data for Orlando downtown simulation shows that the maximum recorded average speed (v_f) is 27.4 km/h and maximum average flow (q_{max}) is 375 (veh/h). In addition, 60 veh/km is the maximum average density, which is recorded at the end of the simulation time period. In order to discuss the calibration result of macroscopic traffic flow models; we consider the following:

- *Which is the best mathematical model that provides best fit to the data,*
- *satisfies the boundary condition,*
- *and yields reasonable estimates of average free-flow speed, maximum average flow, and average jam density.*

Table 4.1: Calibration of macroscopic traffic flow model for Orlando downtown network.

	Model	Mathematical Definition	v_f	k_j	v_c	k_c	q_c	R^2
1	Greenshields	$v = v_f * \left(1 - \frac{k}{k_j}\right)$	25.2	57.2	12.6	28.6	360.4	0.921
2	Conventional Greenberg	$v = v_c * ln\left(\frac{k_j}{k}\right)$	--	70.2	12.1	25.8	312.6	0.925
3	Conventional Underwood	$v = v_f * e^{-k/k_c}$	37.4	--	13.8	23.1	317.4	0.958
4	Underwood with Taylor Series	$v = v_f \left(1 - \frac{k}{k_c} + \frac{k^2}{2k_c^2} - \frac{k^3}{6k_c^3}\right)$	28.0	58.1	9.3	36.4	339.0	0.926
5	Drake Model	$v = v_f * exp\left[-\frac{K}{2k_c^2}\right]$	25.5	--	15.5	22.7	350.8	0.979
6	Drake with Taylor Series Expansion	$v = v_f \left(1 - \frac{k^2}{2k_c^2} + \frac{k^4}{8k_c^4} - \frac{k^6}{48k_c^6}\right)$	19.4	61.2	11.7	32.2	376.8	0.841
7	Polynomial n = 2	$v = v_f + b_1 k + b_2 k^2$	33.0	--	14.2	23.7	337.7	0.981
8	Pipes' Generalised Model n = 2	$v = v_f * \left[1 - \left(\frac{k}{k_j}\right)^n\right]$	18.0	56.4	7.6	32.6	248.2	0.792
9	Pipes' Generalised Model n = 3	$v = v_f * \left[1 - \left(\frac{k}{k_j}\right)^n\right]$	15.5	56.7	11.6	35.7	415.8	0.674

The Pipes' generalised models (n=2 & 3) and Drake model with Taylor series Expansion are excluded from the list due to low goodness of fit (R^2) as well as unrealistic estimate of average free-flow speed. Although, goodness of fit is high, the Conventional Greenberg and Conventional Underwood models are also excluded from the list due to their unrealistic estimation of maximum average flow (q_c). Similarly, Greenshields and Underwood with Taylor series models are excluded due to unrealistic estimation of density at capacity (k_c). Despite model yields a finite jam density when the flow approaches zero, Conventional Drake model is recommended as MFD for Orlando downtown network with high observed goodness of fit ($R^2 \approx 0.98$). It is emphasised here that the result in this analyses have been based on the simulated data gathered from the micro-simulation model VISSIM, however, calibration parameters for real field data of the same study area in Orlando network may yield different values.

4.5.2.2 ***Relationship between MFD and TFM***

As mentioned in Chapter 2, Herman and Prigogine have proposed a simple theoretical relationship to describe dependence of network density (K) on average fractions of vehicles stopped (Fs). This proposed model allowed indirect representation of the macroscopic traffic flow of traffic using the TFM parameters T_m, n, and a parameter p. They proposed that the fraction of stopped vehicles was a power function of network density as shown in (4.34). As the density of traffic network increases the fraction of stopped vehicles, and when the network density reaches to the jam density (k_j), the value of Fs equals 1. The fraction of stopped vehicles can be represented as follows:

$$f_s = \left(\frac{k}{k_j}\right)^P \tag{4.34}$$

where k is the average density of traffic network, and k_j is the network-level jam density. The parameter P reflects the quality of traffic network as it determines the sensitivity of Fs to increasing number of vehicle in network. It is important to clarify that parameter P is different from the other TFM parameters. The higher values of parameter P indicate better quality of traffic service.

From (4.34) and TFM as described in Chapter 3, we can estimate the MFD parameters as follows:

$$V = V_m \left[1 - \left(\frac{k}{k_j}\right)^P\right]^{(n+1)} \tag{4.35}$$

$$Q = k.V_m \left[1 - \left(\frac{k}{k_j}\right)^P\right]^{(n+1)} \tag{4.36}$$

The expressions (4.35) and (4.36) represent the key relations between TFM parameters and MFD. For Orlando network, the parameters of macroscopic traffic flow model V_m (or T_m) and n are obtained from the TFM as mentioned earlier. Similarly, the parameter P was determined through a log (base 10) transformation, which can be applied to both sides of (4.34) followed by a linear relationship between log (f_s) and log (k). The value of parameter P obtained from simulated data for Orlando downtown network was 0.524 with R-square equal to 0.901.

Figure 4.3 and Figure 4.4 show the macroscopic relation between speed, density and flow for Orlando downtown network estimated by TFM and Conventional Drake model with measured values from VISSIM simulations. It should be noted that both analytical models could be used to measure the MFD for different densities. Figure 4.3 illustrates that there is a close match between analytically estimated results and measured ones for speed-density relationship. However, differences can be observed at lower densities, especially for TFM. Even though, the free flow speed estimated by the TFM is significantly high as compared with measured values from simulation; the estimated value $v_f = 47\ km/h$ is relatively close to the network design speed of 60 km/h.

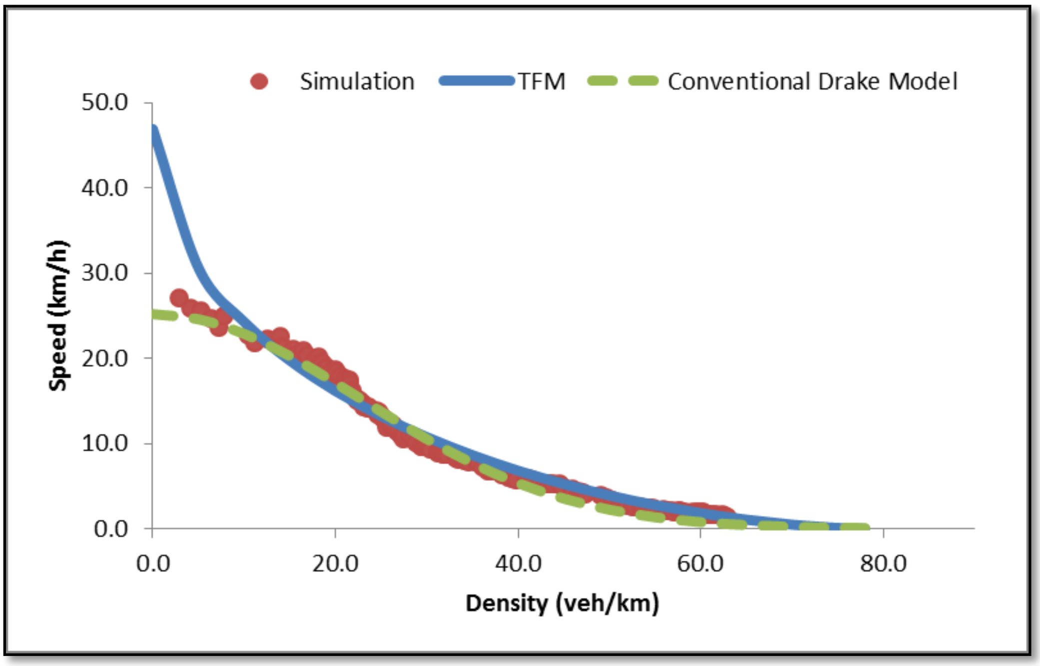


Figure 4.3: Speed-Density plots for Orlando downtown network

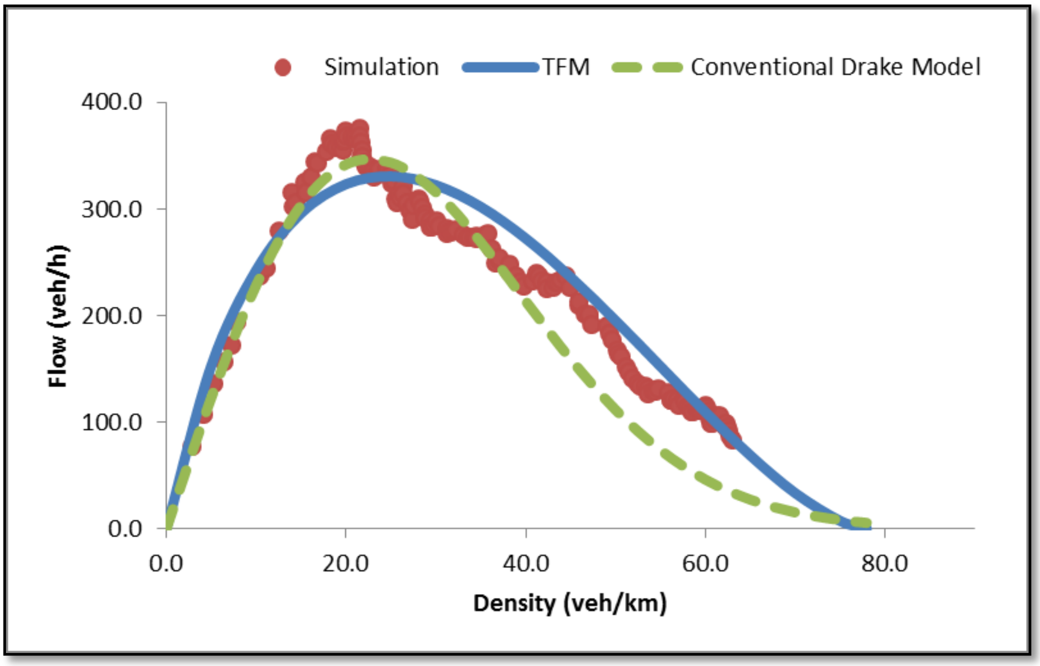


Figure 4.4: Flow-Density plots for Orlando downtown network

Figure 4.5 shows flow-density plots for Orlando downtown network estimated by different methods. There is a good match between analytical estimates and measured values of flow at lower densities, but both of two models show some degree of difference in estimated average flow during saturated and over-saturated traffic conditions. It can be observed from Figures 4.4 and 4.5, that generally the result from Conventional Drake model underestimates the average flow in network. The line fit of the result as compared with simulated data is slightly lower than 1 (y = 0.966 X) with acceptable R squared value (R^2) of 0.89. On other hand, the estimated values from TFM have shown that the result from (4.10) is slightly overestimated the network average flow. The line fit of the result as compared with simulated data is slightly higher than 1 (y = 1.014 X) with better fit to simulated data with R squared value (R^2) of 0.902.

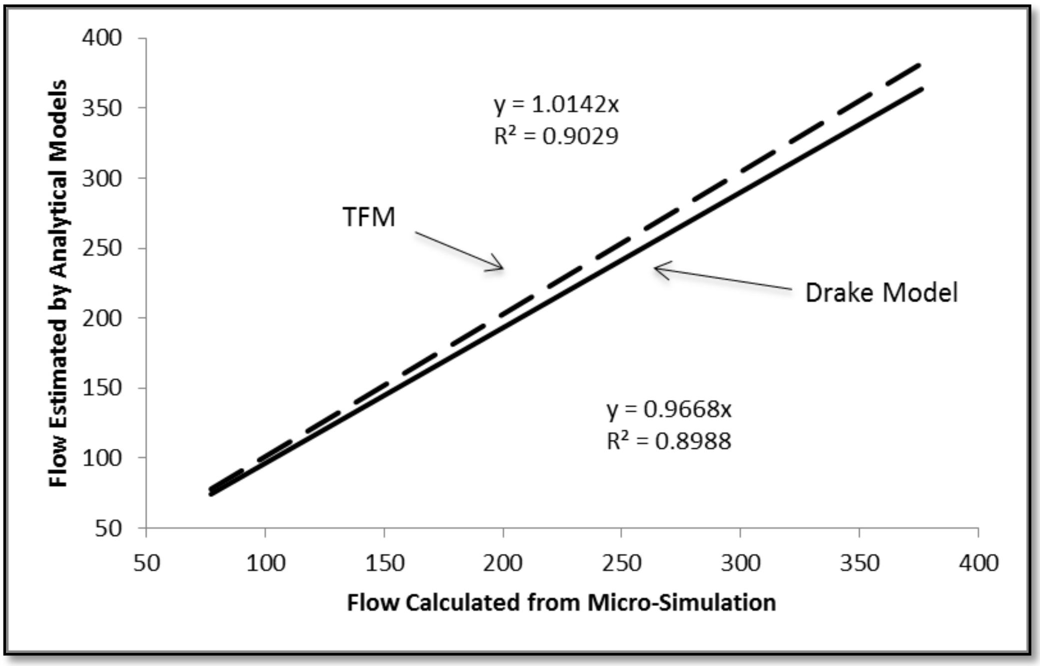


Figure 4.5: Comparison of the average flow estimated by TFM and conventional Drake model with results computed by VISSIM

Table 4.2: Calibration results of TFM and conventional Drake model for Orlando downtown network

Model	Mathematical Definition	v_f	k_j	v_c	k_c	q_c	R^2	MAPE %
Drake Model	$v = v_f * exp\left[-\frac{K}{2k_c^2}\right]$	25.5	--	15.5	22.7	350.8	0.979	20.04
TFM	$V = V_m\left[1-\left(\frac{k}{k_j}\right)^p\right]^{(n+1)}$	46.9	78.0	13.3	25.0	332.8	0.962	10.16

Generally, Conventional Drake model and the TFM have shown a high goodness of fit to measured values from micro-simulation as shown in Table 4.2. The observed values of R^2 are higher than 0.96 in both models. In addition, it is important to note that the two macroscopic traffic flow models have generally satisfy the boundary condition and yield reasonable estimates. Furthermore, the mean absolute percentage error (MAPE) is calculated to compare the accuracy of estimation models to predict the macroscopic traffic states in network. As shown in Table 4.2, MAPE for Conventional Drake model is too high as compared with the result for TFM, where the values are 20% and 10% respectively, where the difference is statistically significant. Considering the MAPE, MFD estimation for Orlando downtown network using (4.35) and (4.36) is considerably better than the Conventional Drake model. Finally, it should be emphasised that the results in this analysis are based on simulated data collected from the City of Orlando. However, real field data results from the same study area in Orlando network may be different.

4.6 Emission Results

The objective of this section is to validate the emission model as proposed in Chapter 3, which can be applied to network-wide emission evaluation. As mentioned earlier, the proposed model estimates the emissions associated with average cruising and idling time from vehicles in traffic network utilising the macroscopic two-fluid traffic model. Vehicles on roads are continuously causing significant amount of the carbon dioxide emissions to the atmosphere. The proposed model can be applied to evaluate CO_2 levels for Orlando downtown network. In addition, this section aims to study the relation between vehicles emission and traffic flow parameters at a network level particularly to discover the impact of increasing urban network density on total emissions rate (E_{total}) and average emissions factor (E_f), which are actually obtained for Orlando downtown network.

4.6.1.1 *Emission Factor Results*

Emission factor represents the average emissions released from single vehicle per unit distance travelled in network for a particular traffic condition. Two different approaches have been applied to calculate E_f in this section. The first one is analytical approach as proposed in Chapter 3, and the formulation of the proposed model is presented above mathematically in (4.30). In the second approach, simulated emissions data from micro-simulation model are used to calculate the emissions every second from vehicles trajectory data, which are collected from VISSIM. The E_f can be computed by dividing the total recorded emissions from all vehicles during the interval by the total distance travelled after aggregating the data on five-minute time intervals.

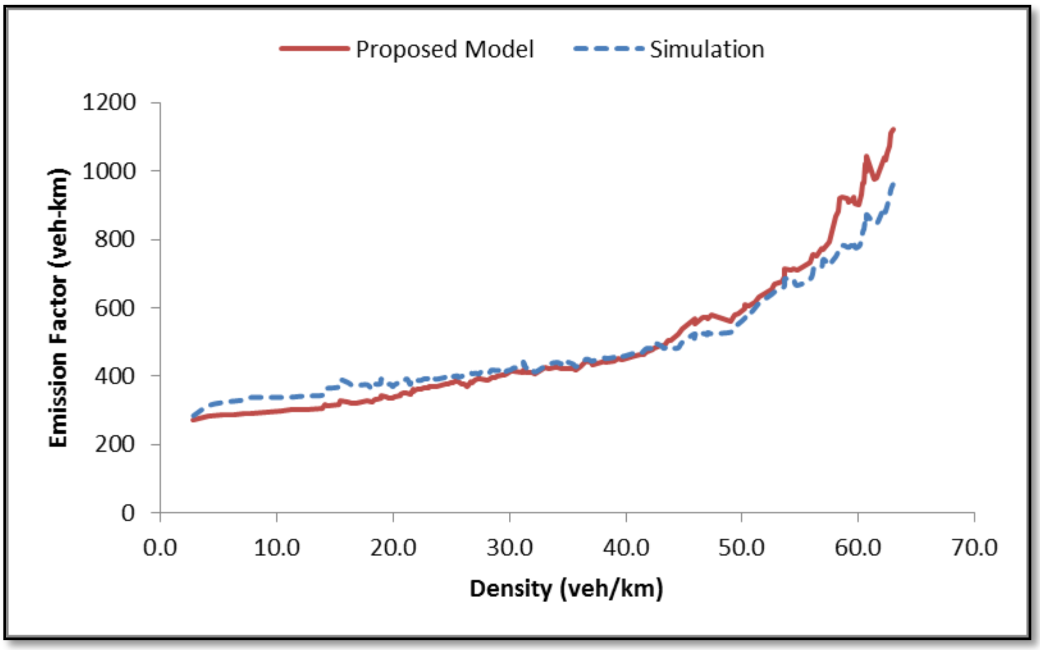
It can be observed that results from proposed model are fairly consistent with the simulated data, which were obtained from second-by-second emission model micro-simulation EnViVer, as illustrated in Figure 4.6.

Figure 4.6(a) illustrates the impact of various traffic densities on emission rate for total simulation time. It can be seen that a positive correlation exists between average network density and average emission rate per distance travelled. Vehicle emission factor (g/veh-km) increases considerably as number of vehicles in network increases, especially at high congestion conditions. It implies that vehicle emission rate per unit distance travelled is sensitive to the level of congestion in urban road traffic network. Although the prediction for the CO_2 from proposed model might not appear accurately at high speeds (free flow conditions), it should be noted that a comparison of the emission estimates for Orlando network indicates that the error is below 12.2% on average as shows in Table 4.3.

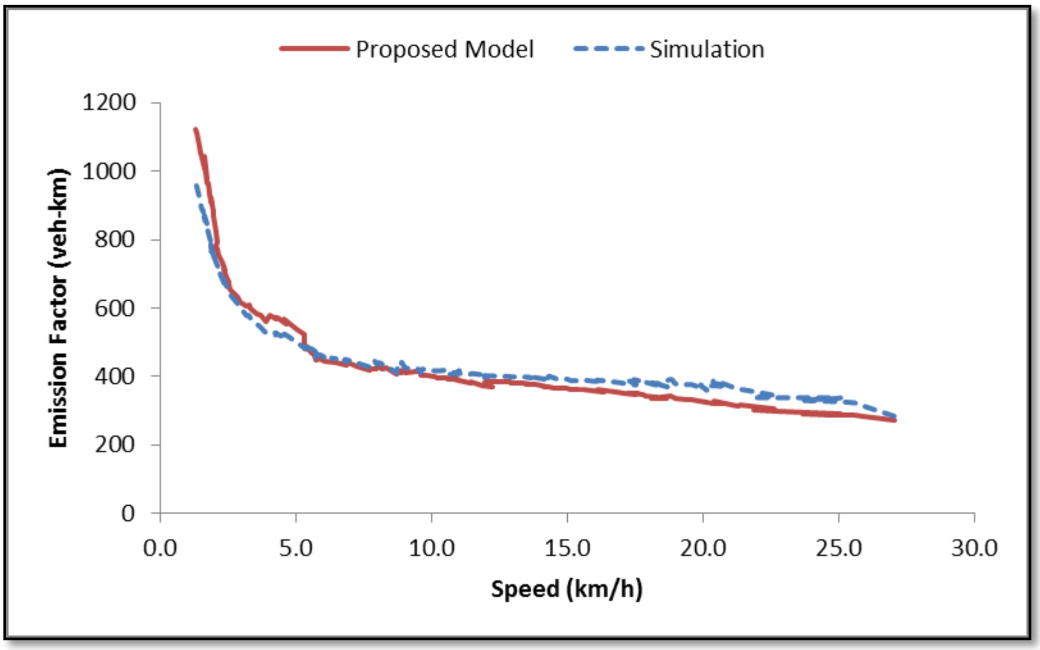
Figure 4.6 (b) illustrates the impact of average network speeds on the average CO_2 factor for vehicles traveling within Orlando network. It is evident from the figure; a negative correlation exists between average network speed and average emission rate per distance travelled. The average vehicle emission factor increases in linear fashion as the average speed of vehicle in network decreases; with a considerable raise especially at high congestion conditions. The emission factor varies from a maximum of 1000 (g/veh-km) at jam density to a minimum of 280 (g/veh-km) at free flow condition.

In addition, simulations depict that the U-shape diagram can be found between the average emission factor and network flow plot. Figure 4.6(c) illustrates that the vehicle emission rate per unit distance travelled rate remains constant at around 285-380 (g/veh-km) with different value of network average flow at free flow state. However, the figure also demonstrates that the average vehicle emission factor increases rapidly during uncongested traffic flow.

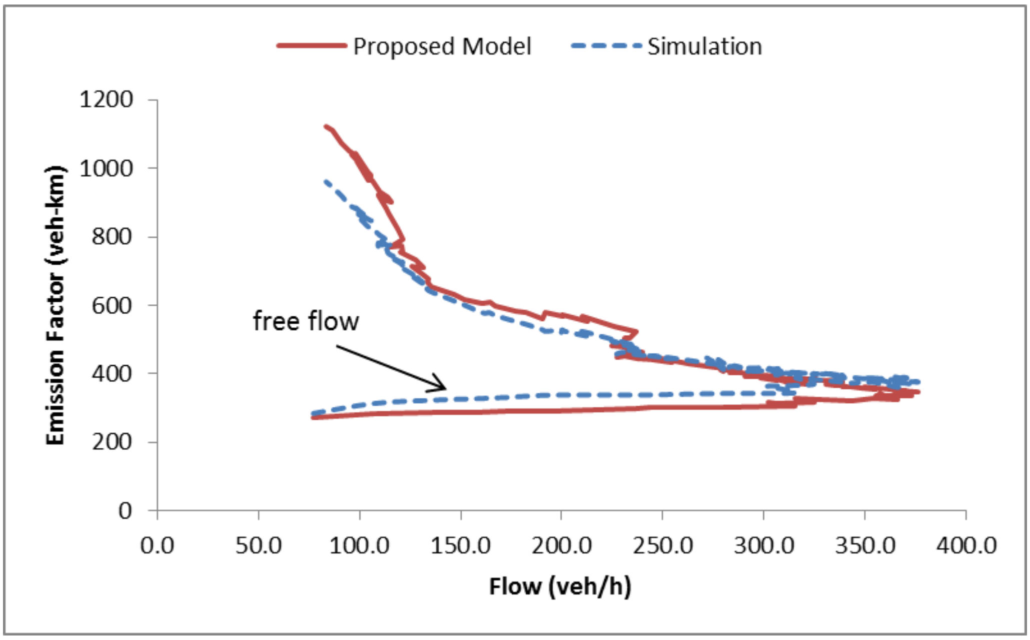
Generally, at any value of average network flow, vehicles in traffic system produces a higher emissions rate at congested regime as compared with free flow condition since the emission factor is positively correlated with average network density.



(a) Average emission factor vs. density



(b) Average emission factor vs. speed



(c) Average emission factor vs. flow

Figure 4.6: Average emission factor vs. MFD for Orlando downtown network

Figure 4.7 presents a comparison between estimated emissions factor obtained analytically from average traffic parameters using the proposed model and the emissions which are directly computed by EnViVer. It can be observed that the proposed model provides reliable estimates as compared with the output of micro-simulation emission model with detailed vehicles trajectories data-sets. The graph demonstrates that the slope of the fit (i.e., line) of the comparison data is slightly higher than 1 (y = 1.0567 X), which indicates that the proposed model slightly overestimates the emission factors during simulation time for in most of the cases, especially when traffic approaches to grid-lock condition. In addition, the proposed model can provide a good estimate of emission factors with an acceptable R squared value (R^2) of 0.941. Thus, it can be concluded that emission factors from aggregated traffic variables are similar to the vehicles trajectories-wise emission calculation.

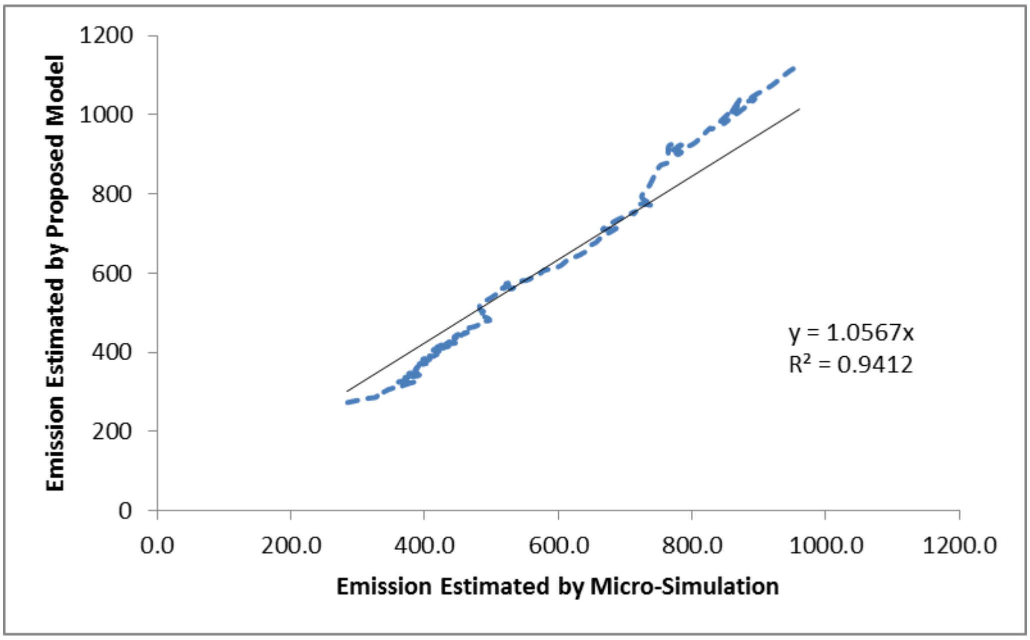


Figure 4.7: Comparison of analytical modelling emission data vs. simulation for Orlando Network

Table 4.3 shows the variation of model accuracy for different level of the traffic network density. The average emission factor (E_f) together with total emission rate (E_{totl}) from proposed model is consistent with the simulated data obtained from second-by-second EnViVer. The results prove that the maximum average relative error observed between two methods is lower than 6.5% for the average network density of 20 to 40 veh/km. Furthermore, the values of modelled emission rate are not significantly different statistically from the measured CO_2 levels from micro-simulation for traffic system performed under such densities. Similarly, the proposed model has computed the emission result with average relative error below 12.5% for densities lower than 20 veh/km. The results show that the highest relative errors of the proposed model observed for near jam density traffic data from field do not show very high-congested level on the network. Such state near complete gridlock is an unrealistic traffic state and traffic engineers don't desire such condition to happen. Finally, it is evident from the numerical results (see Table 4.3) that the CO2 emission values E_f and E_{total} from proposed model are sensitive to the level of congestion in network.

Table 4.3: Error results of proposed model compared to the micro simulation

Density Level	Simulated		Proposed Model				
	Average Emission Factor (g/veh-km)	Sum of Total Emission (kg/Time-Step)	Average Emission Factor (g/veh-km)	Sum of Total Emission (kg/Time-Step)	RMSE	MAE	MAPE %
0 – 10	320	11	286	10	36	34	10.5
10 – 20	369	111	324	97	46	45	12.2
20 - 30	399	273	374	255	26	25	6.4
30 - 40	438	119	426	116	13	12	2.7
40 - 50	503	93	524	97	32	27	5.2
50 - 60	699	115	765	125	82	66	9.0
60 - 70	864	60	1008	70	145	145	16.7

4.6.1.2 *Total Emissions Results*

Total emission variable represents the total emissions from all vehicles travelling in network in each time-step. This important measurement variable evaluates the contributions of local traffic network emissions into total national emissions. Three different approaches have been conducted to calculate E_{total} in this section:

1. First Approach: it is based on analytical results from our proposed model in Chapter 3. The formulation of the proposed model is presented in above methodology as in (4.33). The traffic input data was the aggregated data measured directly from micro-simulation VISSIM.

2. Second Approach: here the same proposed model is used; however, the traffic was estimated from theoretical macroscopic relationship as in (4.35) and (4.36) which were presented earlier.
3. Third Approach: we used simulated emissions data from micro-simulation model that calculate the emissions every second from vehicles trajectory data collected from VISSIM. After aggregating the data to five-minute time intervals, the E_{total} can be directly computed from the total recorded emissions from all vehicles during the interval.

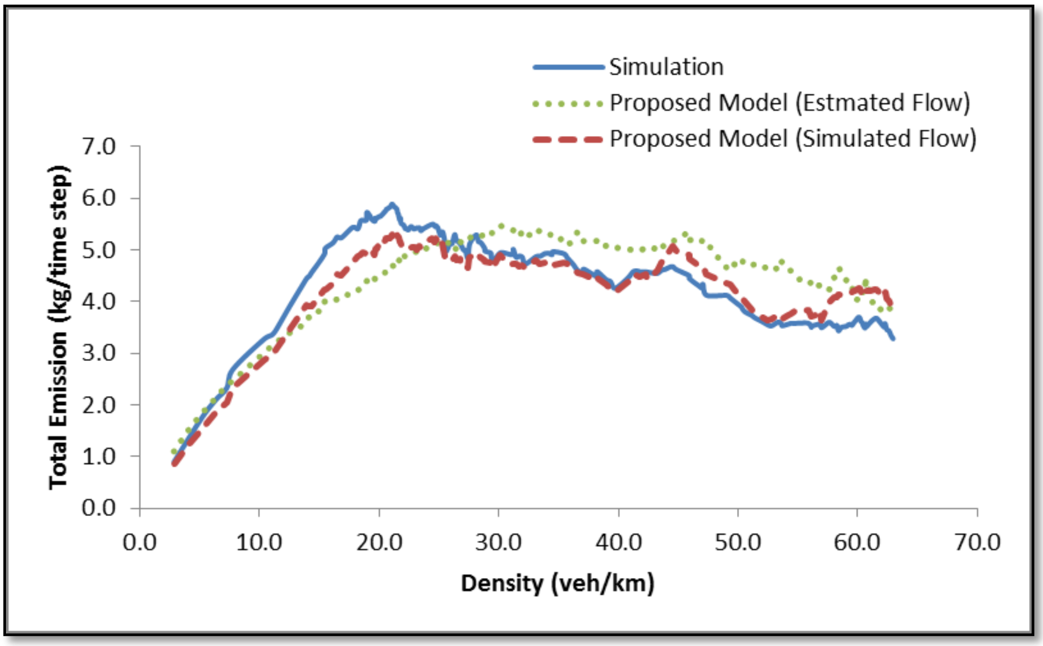


Figure 4.8: Total Emission vs. MFD for Orlando downtown network

Figure 4.8 shows the total emissions released from all vehicles traveling within Orlando network during simulation time obtained from different methods of calculations. Also, the figure demonstrates the relations between total network emissions with macroscopic traffic flow density. The simulation results confirm that the fundamental diagram shape between the total network emissions and network density plot can easily be found. In particular, the E_{total}

increases with increasing number of vehicles in traffic network until the system saturates and reaches its maximum output. Then, the trend is radically refers to negative relationship and gradually the E_{total} decreases when network density increases. This is because of the fact that fewer vehicles are traveling during congestion regime as a result of reduction in average speed and rising of average idling time. However, the change in traffic network performance under congestion conditions is bigger than the decrease in amount of pollutants released by vehicles. This is due to the effect of increasing average idling emission from vehicles in a network. The maximum value of total network emission was obtained near the network sweet spot equal 400 veh/h and density 22 veh/km.

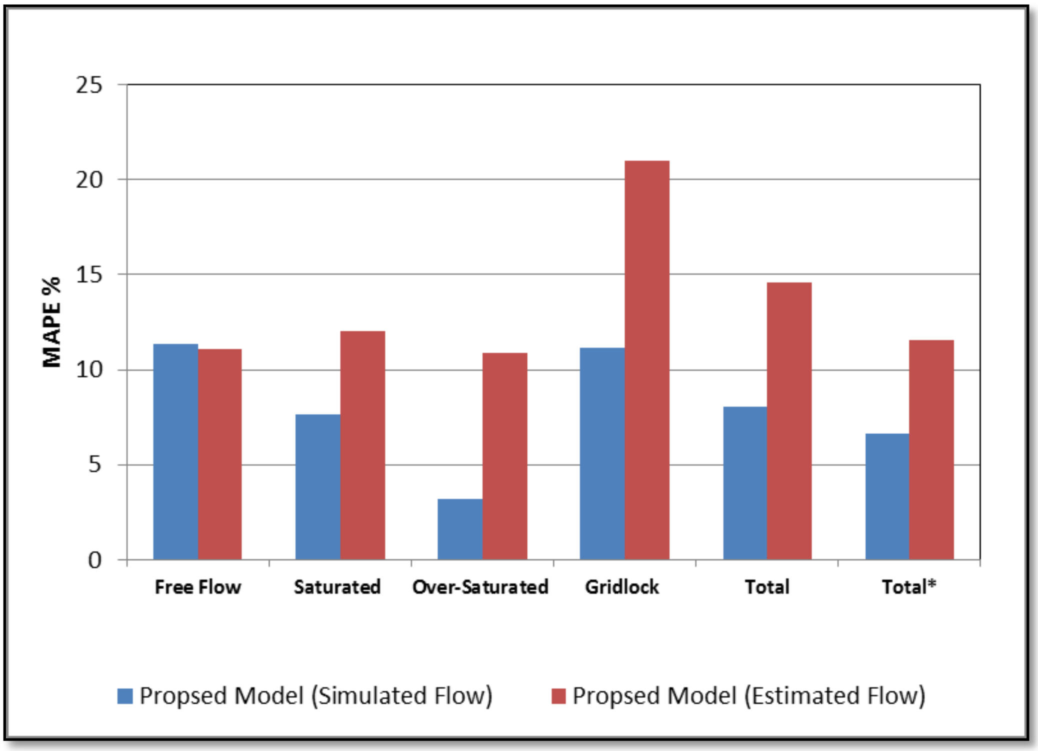


Figure 4.9: MAPE values for different traffic conditions
(* indicate the MAPE for whole run excluding gridlock state)

Figure 4.9 illustrates the mean absolute percentage error (MAPE) measured for different traffic conditions. It is clear from the figure that by excluding gridlock conditions, there is a strong negative relation between network traffic conditions and model accuracy using simulated traffic data, whereas the MAPE values of proposed model based on simulated traffic data remained below 12%. Another point to consider is that the MAPE of the models is very high; however, as we mentioned earlier that this condition is in fact an unrealistic traffic condition. Finally, all of the network data excluding gridlock conditions are combined to come up with more realistic MAPE calculation of the proposed model. The final model result show that the total emissions based on simulated network-average traffic variables are very similar to emissions produced by the microscopic model where MAPE value lower than 7%. In contrast, when the model inputs estimated analytically, the accuracy of proposed model dropped and MAPE raised to nearly 12%. This indicates the importance of reliable representation of traffic conditions in the network in order to estimate total emissions in that network. Also, the outcome indicates that the aggregated traffic parameters of MFD can be used to estimate total emissions in the network.

4.7 Summary

In this Chapter, the application of the proposed model to estimate CO_2 emission rate for Orlando downtown network is demonstrated in detail. The traffic microscopic simulation VISSIM has been used to obtain vehicles trajectory files recorded every simulation second, and the microscopic emissions model EnViVer has been utilised to compute the emission values using the vehicles trajectories. MATLAB software is used to facilitate the analysis.

The analytical model delivered from the TFM is used to evaluate the MFD of Orlando downtown network. The result showed 10.16% error between the average network traffic parameters estimated analytically and simulations and proved a robust relationship between TFM parameters and the MFD properties. In addition, the proposed analytical model has been used to estimate total emissions and emissions per unit of distance. The $E_f$together E_{totl} from proposed model is consistent with the simulated data obtained from second-by-second by micro-simulation. The comparison of CO_2 emission factor measured from analytical modelling shows that there is no significant statistical difference with simulations, and the observed error from the model is lower than 6.5% during a congestion state.

Furthermore, the presented result depicts a positive correlation between average density in the network and emission rate per vehicle-kilometre-travelled. As the number of vehicles increases in the network, the average vehicle emission factor also increases whereas the total emission rate from overall traffic system increases with increasing number of vehicles in traffic network until the system reaches saturation and attains the maximum output. Then the trend radically refers to negative relationship and E_{total} decreases gradually when network density increases.

Finally, it has been demonstrated that the proposed emission model could be applied to large-scale networks, and provides an alternative tool for the air quality assessment. This study has chosen passenger cars to represent all vehicles classes in a network and evaluates the carbon dioxide emission from a selected class. However, the proposed methodology is quite general and can be easily applied to different types of pollutants and vehicles class.

Chapter 5.

Empirical Analyses of the Proposed Model in a Grid Network

The principal objective of this Chapter is to validate the proposed model to evaluate the network wide emissions and to investigate the relationship between vehicles emission and traffic flow parameters at a network level. In particular, this Chapter presents results from the micro-simulation of a grid network with different levels of traffic density scatter (heterogeneity) by introducing various turning movements at the intersections.

An error analysis has been conducted to compare the results from the proposed model with data simulated on microscopic emission model derived from the second-by-second vehicle trajectories generated by micro-simulation traffic model (VISSIM). This analysis takes into account the impact of the estimated traffic parameters using two fluids model (TFM) to the final output from the proposed model. The result of the analysis is consequently utilised to evaluate the robustness and consistency of model outputs. Thus, various sources of errors as well as their influence on the final results are examined in detail.

5.1 Network Description

In this Chapter, a square grid network is constructed and performed in VISSIM simulation software. The network is a 6 x 6 grid with a number of roundabout intersections with uniform settings. All intersections have a similar number of lane and width, and have identical conflict areas set, such as time and priority, and reduce speed zone. The network consists of 250 one-way links where each link has one lane of length ℓ = 250 m and the total network length is around 25 km. The network layout is shown in Figure 5.1.

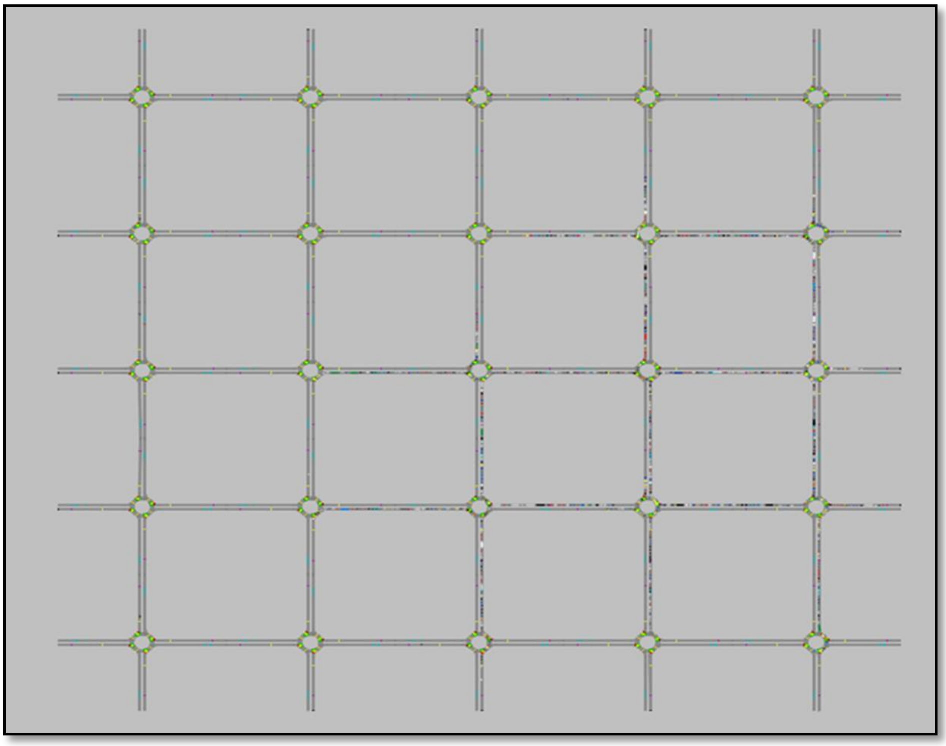


Figure 5.1: Snapshot of idealised network layout in VISSIM

Having identical number of vehicles fed into the network via each link ensures a uniform loading throughout the network. Therefore, the traffic demands in the network are evenly and spatially distributed. There are three different scenarios proposed in this experiment. Within each scenario, different simulations run with various random seeds were performed, and all simulations were run for one hour simulation time. A 5-minute time-step is used in all runs.

In the first scenario, all vehicle-turning movements are banned and only through passes are allowed at all intersections in order to have an idealised network. Therefore, the traffic conditions on the proposed network in this scenario remain homogeneous, and the simulation result represents a well-defined MFD for the network. On the other hand, all three movements' types such as right-turn, left-turn and through passes are permitted in the second scenario in order to obtain a random distribution of vehicle density over the network; hence the well-defined MFD assumption is then relaxed. The percentages of turning movements are 10% right and 20% left at all intersections. Lastly, U-turns movements are allowed with a percentage of 10 % in addition to right-turn and left-turn in the third scenario.

5.2 Simulation Results

The VISSIM is used to obtain the network traffic performances from the vehicles trajectory aggregated data based on five-minute time intervals. The macroscopic fundamental diagram model (MFD) is computed for each scenario.

Figure 5.2 shows that a well-defined MFD exists from the simulation in the first scenario, where the scatter are relatively low at all different traffic regimes such as free flow, optimal throughput (saturated) and congestion (over-saturated). Whereas the scatter of the MFD is increased with increasing percentage of turning movements, as well as the average network flows are relatively low at higher densities when turning movements are permitted. This is because of the fact that the spatial inhomogeneity of density impacts the networks average flow due to unevenly distributed congestion over network. The reason for that is some links of the network may reach total gridlock condition while other links are not congested yet. However, as shown in Figure 5.2, a limited effect of turning movement on the network's average flow is observed at free-flow condition due to the absent of queue spillbacks.

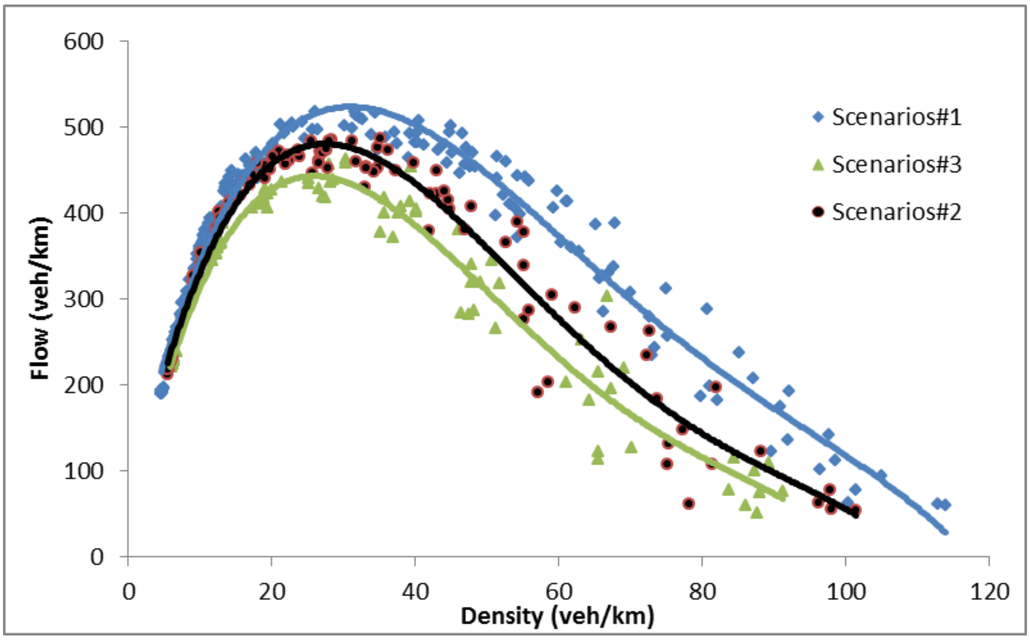


Figure 5.2: Relationship between network flow and density measured from the simulation for three different scenarios

In Figure 5.2, the maximum average flow was 550 veh/h occurred at critical density of network when average density was 27 veh/km for the 1st scenario, whereas the 2nd scenario q_{max} was 480 veh/km and K_c was 25 veh/km, and in 3rd scenario q_{max} was equal to 420 and K_c was 22 veh/km. This result clearly shows that there are three different MFDs to the network even though in all three scenarios the proposed network is subject to the same infrastructure, traffic controls and vehicles input. This is because of turning movements, which cause uneven distribution of vehicles with time that significantly impacts the network performance. This shows that the MFD shape can be influenced by traffic heterogeneities. It raises the importance of investigating the effect of the shape of MFD on proposed model, and to examine the effect of turning movements in the network on traffic parameters estimation and emission calculations. In general, with the compaction of three scenarios, 1st scenario performs remarkably better at all traffic conditions.

Figure 5.3 shows the variation of total network density for different scenarios during simulation period. Although in all scenarios, the traffic demands in the network are similar, 2nd and 3rd scenarios approached gridlock condition faster than the 1st scenario. This is because of the lesser scatter of vehicle density in the network, which has tremendous direct impacts on the performance of the system. For further detailed, experimental investigation of the impact of heterogeneity, MFDs have been conducted using real data from a French city (Buisson and Ladier, 2009).

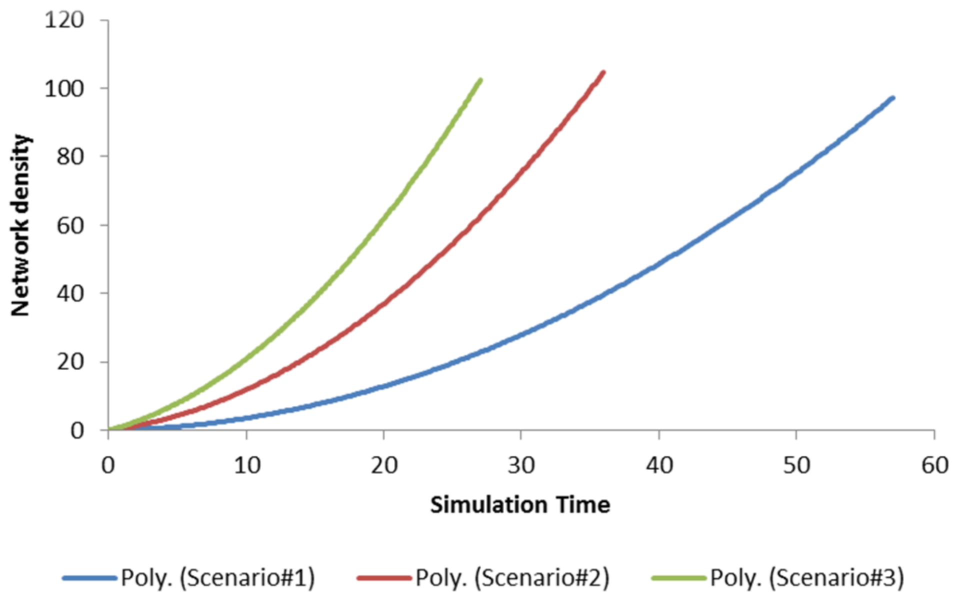


Figure 5.3: Variation of network densities vs. simulation time for three different scenarios

5.3 Statistical Evaluation of the Effect of the Heterogeneity on Traffic Parameters Estimation

The two-fluid model (TFM) is used to describe the relation between travel time per unit of distance and stopped time per unit of distance. This section examines the accuracy of the average cruising and idling time predicted using this TFM, and discusses sensitivity of the estimates of the two fluid parameters to various scatter of MFDs. Even though a number of studies have applied TFM in different road networks around the world, it is still important to explore whether or not there exists a statistically significant difference between the TFMs to represent homogeneous and heterogeneous traffic conditions.

In Table 5.1, the TFM parameters were calculated using linear regression in order to estimate an average behaviour. Based on the regression analysis, the estimated parameter n was found to be 0.562 in 1st scenario. On the other hand, the value of the parameter n is 0.506 and 0.372 for 2nd and 3rd scenario respectively. The estimated parameter Tm among all scenarios has slightly changed since that the network topology and roadway geometrics of proposed network are fixed, this indicates the free flow speed of the networks is relatively similar in all scenarios. This result shows that more reliable parameters' estimates of TFM are obtained when there exists the well-defined MFD on the network. In addition, we have found that the parameters of the TFM to be significantly correlated with the spatial homogeneity of density in the network. In general, the accuracy of estimation decreases with increasing percentage of turning movement. . This implies that the TFM is sensitive to the level of traffic density-scatter in a network. In addition, F-test is used to evaluate the two-fluid model (TFM) for different scenarios. F-statistic examines the significant linear regression relationship between variable logTr and the variable logT. The p-value of the F-statistic is 0.00 less than 0.05, which indicates that the prediction of the TFM is statistically significant at the 5% significance level for all scenarios. Similarly, table 5.2 shows that for all scenarios the p-value from the t-test analysis is less than 0.05, which indicates that the TFM coefficient is statistically significant.

Table 5.1 Two-Fluid parameter estimation for three different scenarios

Network	***Number of Observations***	***Parameter Estimate***		***R Square***	***F test***	***P Value***	***n***	***Tm (sec/km)***	***Vm (km/h)***
		A	***B***						
Scenario No.1	**160**	**1.26**	**0.360**	**0.946**	**2768**	**0.000**	**0.562**	**93**	**39**
Scenario No.2	**83**	**1.32**	**0.336**	**0.918**	**904**	**0.000**	**0.506**	**97**	**37**
Scenario No.3	**60**	**1.454**	**0.271**	**0.877**	**414**	**0.000**	**0.372**	**99**	**36**
Pooled	**303**	**1.310**	**0.338**	**0.921**	**3492**	**0.000**	**0.509**	**95**	**38**

Table 5.2: Statistical Summary for Two-Fluid parameter Estimates

Network	***Parameter Estimate***	***Coefficients***	***t test***	***P Value***	***95% Confidence Interval***	
					Lower Bound	**Upper Bound**
Scenario No.1	**A**	**1.26**	**80**	**0.000**	**1.23**	**1.292**
	B	**0.360**	**52**	**0.000**	**0.347**	**0.374**
Scenario No.2	**A**	**1.32**	**51**	**0.000**	**1.268**	**1.369**
	B	**0.336**	**30**	**0.000**	**0.314**	**0.358**
Scenario No.3	**A**	**1.454**	**46**	**0.000**	**1.392**	**1.517**
	B	**0.271**	**20**	**0.000**	**0.254**	**0.298**
Pooled	**A**	**1.310**	**100**	**0.000**	**1.285**	**1.336**
	B	**0.338**	**59**	**0.000**	**0.326**	**0.349**

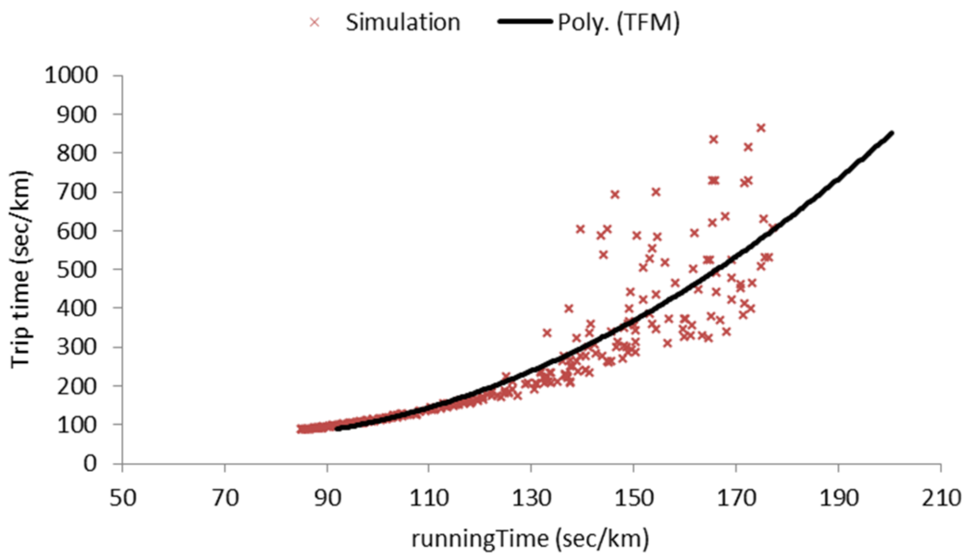


Figure 5.4: Comparison the trip time vs. the running time estimated from TFM the simulated results for the pooled cases

Figure 5.4 shows a graphical representation of the TFMs for the pooled cases. This comparison of the total trip and cruising time estimated using TFMs with measured values from micro-simulation. As shown in the graph, there is a close match between the estimated and measured values, especially for the lower trip time at the free-flow regime. However, the plot scatter rises significantly with increasing average travel time. This is because of the fact that the spatial heterogeneity of density in the network increases with increasing number of vehicles entering networks. On the other hand, there is a clear consistency in the estimation of the total idling time, which can be observed in Figure 5.5. The under-estimation or over-estimation of cruising time can cause estimation errors in emissions rate since cruising time has a high contribution in emissions.

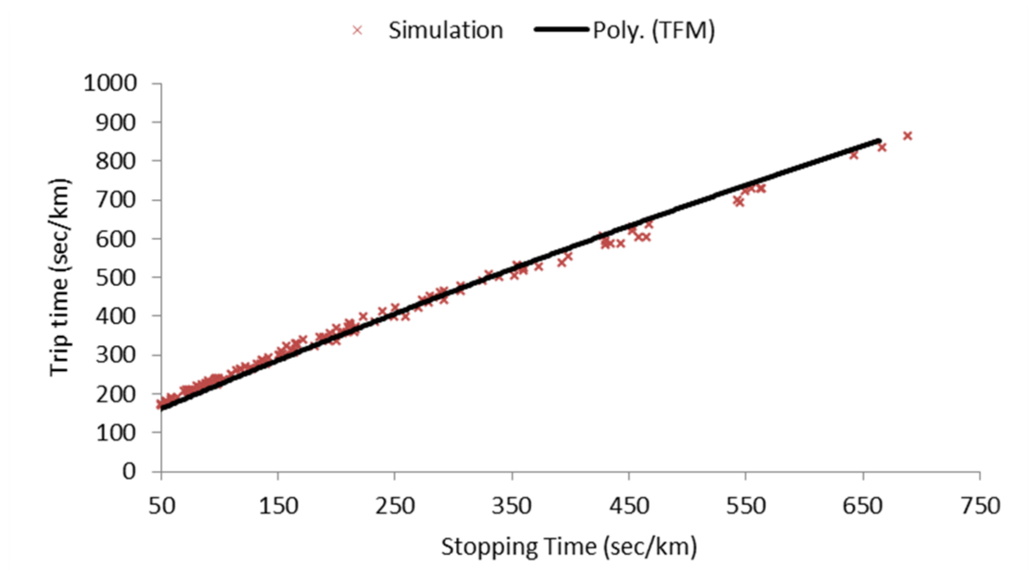


Figure 5.5: Comparison the trip time vs. the stopping time estimated from TFM the simulated results for the pooled cases

5.4 Model Evaluation

5.4.1 Emission Result

With raw vehicle trajectory data, the emission rate per vehicle-kilometre for carbon dioxide (CO_2) was computed for various scenarios using micro-simulation emission model 'EnViVer'. Again, the emission rate for each scenario is computed every 5 minutes, and then also computed for each scenario using the proposed emission model utilizing the average traffic parameters.

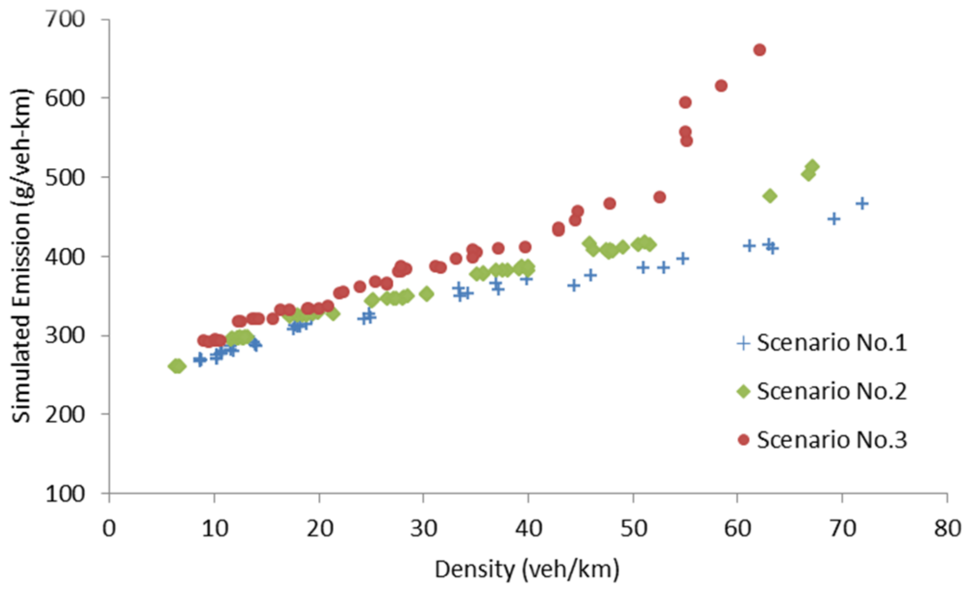


Figure 5.6: Simulated emissions factor vs. network densities for three different scenarios

Figure 5.6 illustrates emission factor variations during simulation period at the grid network based on collected data from traffic simulator VISSIM. The trend shows a similar pattern of the emission factor for grid network in all scenarios that can be observed on the downtown Orlando network as discussed in previous chapter. Also, a positive relationship exists in all scenarios between the network density and emission rate. Furthermore, all scenarios have rather similar rate of emission at lower network densities, with scenario 2 having larger emission rate during higher densities and scenario 3 noticeably having the greatest rate of emission particularly during very high densities. For instance, the average emission rate from vehicles computed from scenario 1 during average network densities equal to 12 veh/km is 280 grams of CO_2 per distance travelled, which closely matches with the scenarios 2 and 3 of approximately 294 and 316 g/veh-km respectively. On the other hand, in scenarios 2 and 3, the average emission factor of vehicles traveling during high network densities, i.e., 60 veh/km, has increased by 15.5% and 59.6%

respectively as compared to scenario 1. The results are significantly different for scenario 3, with higher percentage congestions. It is clear from Figure 5.6 that the emission rates for different scenarios have different magnitudes, and the result indicates that the change in percentage of vehicle turning movements in network accordingly results in a change in emission rate. The reason behind the phenomenon is that the emission rates vary with different distribution of vehicles operating mode. This is because more complex driving behaviour accrues with increasing turning movements.

The proposed emission model is used to estimate the emission of $\mathrm{CO_2}$ pollutant for each scenario. The operating mode emission parameters (e_r and e_s) as in chapter 3 are used during emission evaluation. Figure 5.7 compares the emission rate during consecutive 5-minute intervals by corresponding average vehicles activates. According to this figure, change in estimation of emission rate can be seen among different scenarios, and the emission rate varies in each scenario with different network densities. This difference results from the change of turning movements' percentage at the intersections, and shows to be captured by the proposed model. For example, the emission factors from the proposed model for scenarios 2 and 3 have generally a higher proportion of emissions as compared to scenario 1, which indicates that the proposed model is capable of obtaining the effect of various traffic operations due to different levels of heterogeneity in network traffic density. This shows that the proposed model based macroscopic traffic parameter is able to detect the vehicle emission rate with reasonable degree of accuracy.

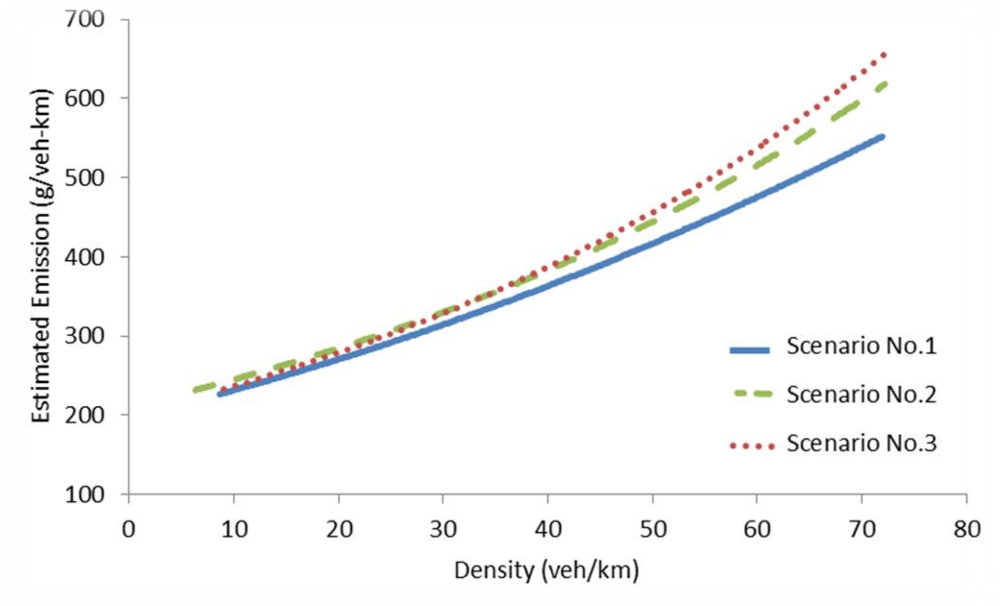


Figure 5.7: Estimated emissions factor vs. network densities for three different scenarios

5.4.2 Verification of the Model

In this section, evaluation of the proposed model is presented. A graphical representation can be utilised to perform a visual comparison of the emission factor (g/km) in each scenario obtained from different methods of calculations, analytically estimated from the proposed model and simulated by EnViVer.

As shown in the Figure 5.8, for scenario 1, the proposed model provides close results with simulated data results, and the dots are mostly distributed along the diagonal line y = 1 X in scenario 1. In general, the proposed model is slightly under-estimating the emission rate in comparison with the simulated data, whereas the proposed model over-estimates the emission at high value of emission rate where the traffic in network is approaching to complete gridlock conditions. The reason behind this over-estimation in emission rate is that the TFM over-estimates the average time spent running from vehicles at very high densities. As Figure 5.9 shows, by comparing running time estimated from TFM model with simulated data using microscope traffic model VISSIM, the TFM over-estimates the values of T_r at higher trip time.

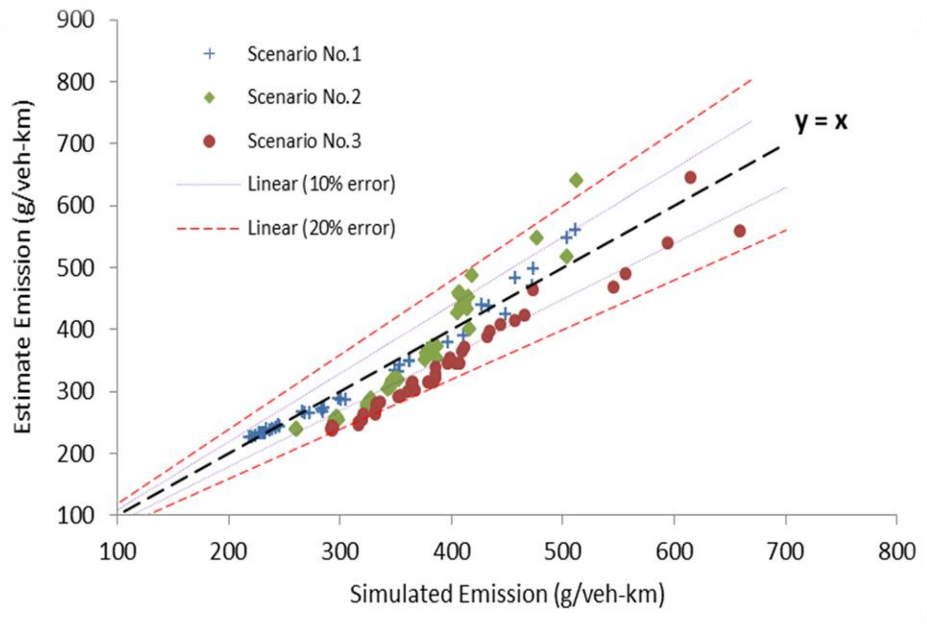


Figure 5.8: Comparison of the emissions factor estimated with the emissions factor computed by EnViVer

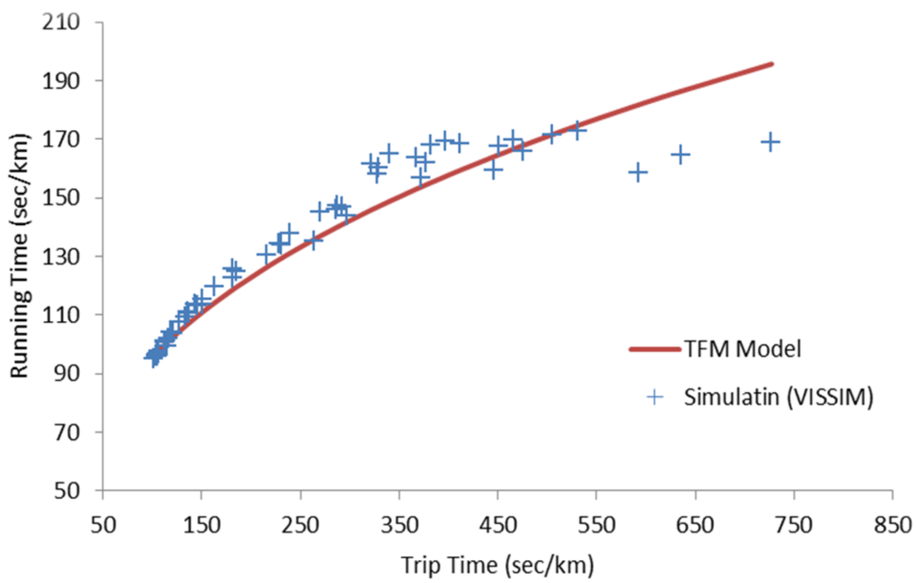


Figure 5.9: Comparison the trip time vs. the running time estimated from TFM the simulated results in first scenario

As shown in Figure 5.8, the error associated with emission estimation by the proposed model is less than ±10%. First scenario represents homogeneous traffic conditions with lower network density scatter. Therefore, the proposed model can reliably estimate network emission rate when the well-defined MFD exists on the network. In addition, it can be observed from Figure 5.8 that the proposed model remarkably under-estimates the average emission factor in grid network in scenario 3 on continuous basis. Similar to scenario 1, a strong linear relationship exists between these two different methods to evaluate emissions in scenario 3. However, by comparing estimated emissions in the network with the simulated data, the model error of the emission estimation was mostly between the range $\pm 10\%$ to $\pm 20\%$ spatially at free flow and saturated conditions. However, the comparison between simulated data and the TFM model graphically show that the TFM yields the almost accurate result with VISSIM for T_r and T_s during free flow and saturated state (see appendix B). This indicates that the average cruising and average idling time is been predicted using this TFM in scenario 3 accurately. The reason behind this under-estimation in emission rate is that the higher percentage of turning movements has increased complexity of driving behaviour in a network. As a result, the intensity of the acceleration/deceleration is dramatically increased during simulation period due to unrealistic stop and go traffic phenomenon. Hence, the vehicles intent to release additional emissions associated with such phenomenon. Therefore, the proposed model does not provide an accurate estimate of emissions, and the result show some level of error (10-20%) comparing to micro-simulation model where the detailed driving behaviour of the vehicles in network is highly considered.

Furthermore, Figure 5.8 shows, the unit of pollutant per unit of distance of CO_2 shows remarkable under-estimation at free flow regime and remarkable over-estimation at the over-saturated regime for scenario 2, while the model fits the simulated data well at the saturated condition. Also, a similar trend appears while comparing the emission rate estimated from the model with the results computed microscopically in Orlando downtown network. This implies that the error in emission estimation from proposed model is dependent on congestion level.

In conclusion, the overall result from all different scenarios implies that the vehicle emission rate per unit distance travelled is sensitive to the level of traffic heterogeneity due to turning movements in addition to the level of congestion in urban road traffic network. In addition, the result shows that the highest error from the proposed model within each scenario is observed near jam densities. However, such very high densities do not appear in real traffic field data.

5.4.3 Errors in Emission Parameters

The parameters e_s and e_r in the proposed model present emission rate (g/h) associated with idling and cruising mode respectively. Previously in Chapter 3, model calibration was performed to ensure that model could estimate the traffic emission reasonably well. A complete driving cycle sets include cruising and idling, which were utilised to present the average performance of the vehicle while traveling on a network. For example, the Federal Test Procedure (FTP) drive cycle "FTP-72 cycle" and the Environmental Protection Agency (EPA) "New York City cycle". The values of model parameters of the pollutant CO_2 for light-duty vehicles (LDVs) class were 8640 and 575 g/h for e_r and e_s respectively. These values were calculated using the microscopic emissions model VERSIT+ (EnViVer software).

This section represents an approach to validate these parameters used in the proposed model. Re-calibration has been performed to compare the emission parameters used in the proposed method and result from 'EnViVer' for each scenario. Then, the errors on total emission of each scenario are tested to investigate whether the default calibration parameters are acceptable or not. The objective of this approach is to observe ability of the proposed model to predict the change in traffic conditions relative to level of heterogeneity caused by various percentage of turning movements at the intersections.

The Table 5.3 shows a comparison of the error in emission parameters (e_r & e_s) with default calibration parameters as in Chapter 3. In addition, it shows error computed for total emission analytically estimated by the proposed model compared with micro-simulation emission result.

Table 5.3: Percent error of model parameters and estimated total emission

		Total Emission (kg)	***Running Emission rate (g/h)***	***Idling Emission rate (g/h)***
Scenario No.1	***Simulated***	12419	8821	534
	Estimated	11906	8640	575
	% Error	-4.13%	-2.06%	7.68%
Scenario No.2	***Simulated***	15255	8147	911
	Estimated	14314	8640	575
	% Error	-6.17	5.70%	-58.49%
Scenario No.3	***Simulated***	10133	9745	1043
	Estimated	8584	8640	575
	% Error	-15.29%	-12.80%	-81.15%

For the 1st scenario, the comparison shows that the proposed model provides close results and slightly under-estimating the total emission with error less than 5% as compared with simulated emissions. Similarly, the error in the proposed model parameters was 2.06% and 7.68% for running and idling mode respectively. In general, the comparison result verifies that the proposed method yields the exact same result as in the 1st scenario. This indicates the proposed method is valid in the case of low scatter MFDs and can compute emissions without the need of further updating the model parameters.

For the 2nd scenario, running mode parameter from re-calibrated results is found similar to default value, whereas the error observed is significantly larger for idling mode (e_s) than that of default value 575 g/h whereas the result from re-calibration is found to be 911 g/h with errors close to 58%. However, based on the total emission result, the error in model parameters are not statistically significant in 2nd scenario, since the proposed model provides a good estimate of total emission and the result show some level of error (<7%).

Finally, considering the 3rd scenario, the proposed model appears to be under-estimating the total CO_2 emissions, with significantly larger relative error equal to 16%. In addition, the error in the proposed model parameters is insignificantly higher, 12.8% and 81% for running and idling mode respectively. This implies that the application of the proposed model on traffic network with high level of heterogeneity of network density may require recalibration approach to enhance the model prediction.

In conclusion, errors generally increase with the increased proportion of turning movement. This indicates that the errors in emission estimation are dependent on levels of heterogeneity of network density. For 1st and 2nd scenarios, the re-corrections on the proposed model parameters are not necessary since the overall error is not insignificant statistically. However, it is clear that large bias only occurs in 3rd scenario with relatively higher percentage of turning movements.

5.5 Summary

This Chapter has presented the results from the micro-simulation of a grid network with different levels of traffic density scatter by introducing various turning movements at the intersections. The effect of traffic conditions on cruising time and traffic emissions are evaluated for a grid network. As expected, we find that the TFM in homogenous traffic conditions is remarkably different from that developed in non-homogenous conditions. We also find that the level of scatter in cruising time is highly correlated with traffic characteristics in the network. This explains the resulting biases caused by developing a TFM as a single model representing all different traffic regimes such as free flow, saturated and over-saturated. However, a TFM results using idealised network match well to simulated traffic data at saturated regimes.

Although there are no differences in road type, control and traffic demands, the levels of traffic density scatter seem to be an important factor in the relationship between prediction error and congestion level. Thus, during modelling the vehicular emission, it is necessary to distinguish between homogenous and non-homogenous regions, since the vehicle emission rate per unit distance travelled is sensitive to level of network heterogeneity.

In addition, the proposed model performs well and shows high accuracy of emission prediction in homogeneous networks. In order to address the limitation of the proposed model in non-homogeneous network, traffic network spatial partitioning technique with regard to definition of well-defined MFD can be utilised to divide the network into multiple homogeneous sub-networks with similar traffic conditions.

Furthermore, the results show that the proposed model provides an approximation of total emissions within 5% of the estimates from the detailed microscopic emission analysis in the case of low scatter MFDs. On other hand, the proposed model appears to be under-estimating total CO_2 emissions, with significantly larger relative error equal to 16% when traffic network performs under high level of heterogeneity.

In conclusion, the overall result from this Chapter implies that vehicle emission rate per unit distance travelled is sensitive to level of traffic heterogeneity due to turning movements in addition to the level of congestion in urban road traffic network.

Chapter 6.

The MFD and Vehicular Emission Relationship

In this Chapter, a relation between traffic road emissions and the average flow, density and speed of vehicles in the network has been determined based on the macroscopic traffic parameters with the sole objective of exploring the macroscopic relationship between the macroscopic fundamental diagram (MFD) and vehicular emissions. We focused on CO emission rate from vehicles using field data. The CO emission rate was considered due to the great harm of CO emissions on both environment and human health. This study was based on data collected for from road tunnels on arterial roads in Riyadh city; the capital of the Kingdom of Saudi Arabia. Field measurements of traffic characteristics have been conducted in a road tunnels by The Closed-Circuit Television (CCTV) system. Air monitoring devices have been utilised to measure the carbon monoxide concentrations inside tunnels.

6.1 Study Area

The field data have been collected from three different road tunnels in Riyadh in Saudi Araba. Two tunnels chosen are located on Al Urubah road while the other is located on Abu Bakr Al Siddiq road. Figure 6.1 shows that the two arterial roads are connected by cloverleaf interchange. These two roads have similar characteristics and conditions. In each direction, they have 3 lanes with average width 3.6m as well as 2.8m width of emergency lane. Roads are equipped with advanced traffic management systems, which have been used to monitor and control traffic flow. For example, the roads are equipped with 260 fixed cameras and 34 coaxial cameras. In addition, the roads are equipped with 161 functional and instructional variable messages.

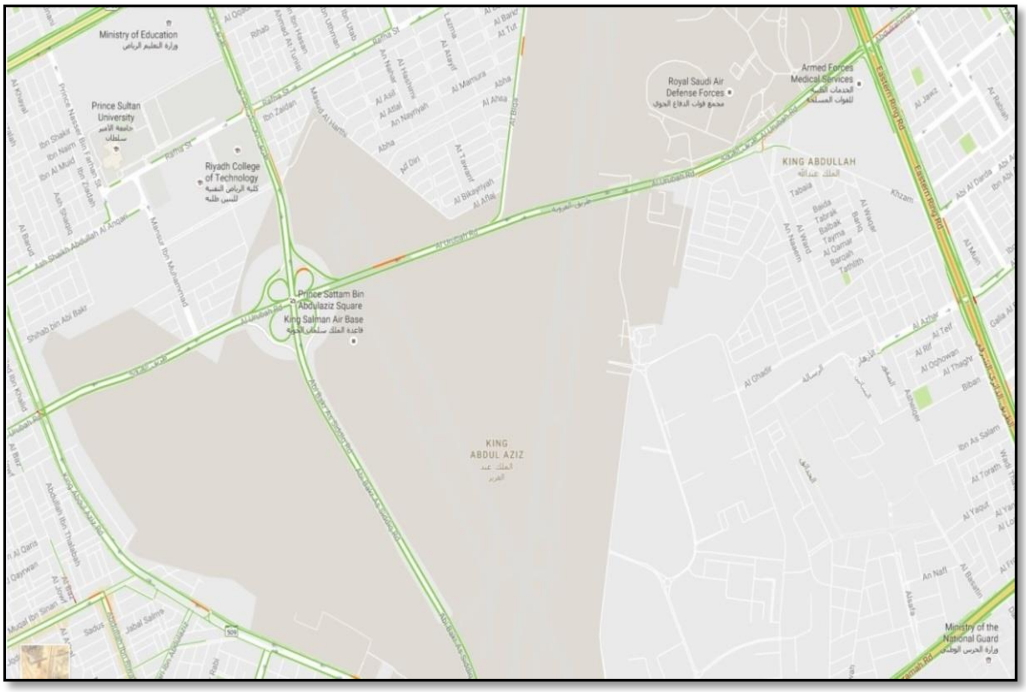


Figure 6.1: The Google map of study area in Riyadh, Saudi Arabia

As shown in Figure 6.2, the tunnels T1 and T2 are located on Al Urubah road with lengths 400m and 500m respectively, while the tunnel T3 is located on Abu Bakr Al Siddiq road with 800m length. Each tunnel contains a CCTV system to monitor traffic as well as an air monitoring devices to measure the carbon monoxide concentrations inside tunnels. In additions, the roadways in tunnels are levelled with no grade.

Figure 6.2: The sampling location of the study area

Also, the tunnels are equipped with a ventilation system to maintain air quality. The ventilation in each tunnel is provided by system of fans moving the air from the entrance to exit of the tunnel. The air flow induced by the fans is one-directional and the vehicle travelling through the tunnel provides additional air movement. There are sets of fans located in the middle of the tunnel and approximately 150m away from the entrance and exit. The concentration of CO emissions was measured continuously at the tunnel's entrance and exit. Two sampling anemometers located inside of each tunnel, approximately 50m away from the entrance and exit did the measurement of air velocity in the tunnels. The Air monitoring devices at both ends were located on top of the tunnel gates; hence providing measurements at every change in sensor reading.

Figure 6.3 A Sample of the Road tunnel (T2)

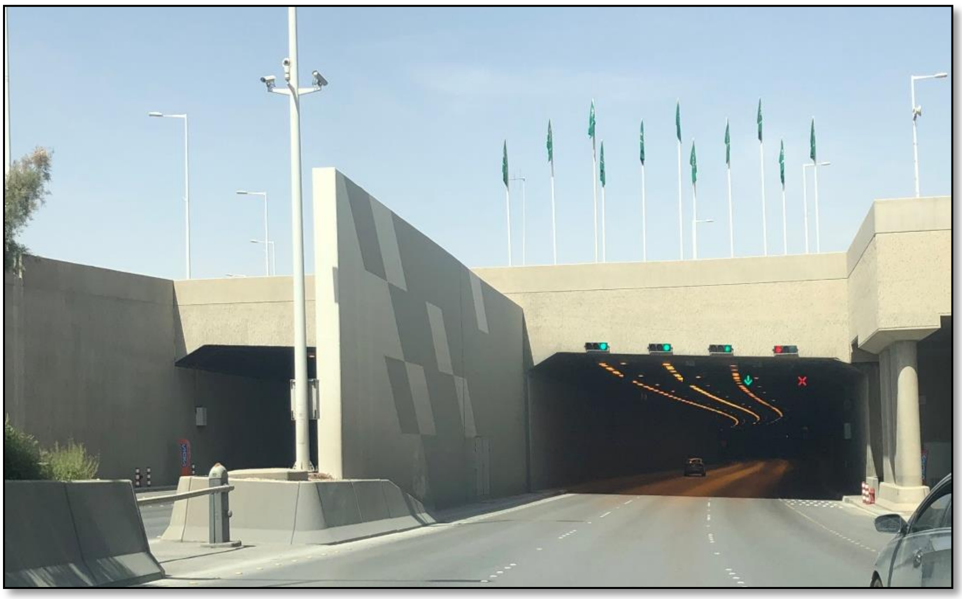


Figure 6.4 A Sample of the Road tunnel (T1)

6.2 Data Collection and Description

Data were provided by the Central Control Room (CCR) of ArRiyadh Development Authority. They have number of control rooms operating on a 24/7 basis controlling and monitoring the major arterials roads in Riyadh city. All data are available in central database for 6 months. Each tunnel contains a Closed-Circuit Television (CCTV) system to monitor and count traffic. In addition, air monitoring devices are used to measure the concentration of pollution inside tunnels.

Traffic data and emission data were obtained from the CCR of Saudi Arabia ADA database. The CCR system creates two separate reports every one hour. One represents the traffic flow conditions and another for air quality conditions. Figure 6.5 shows the Central Control Room from inside.

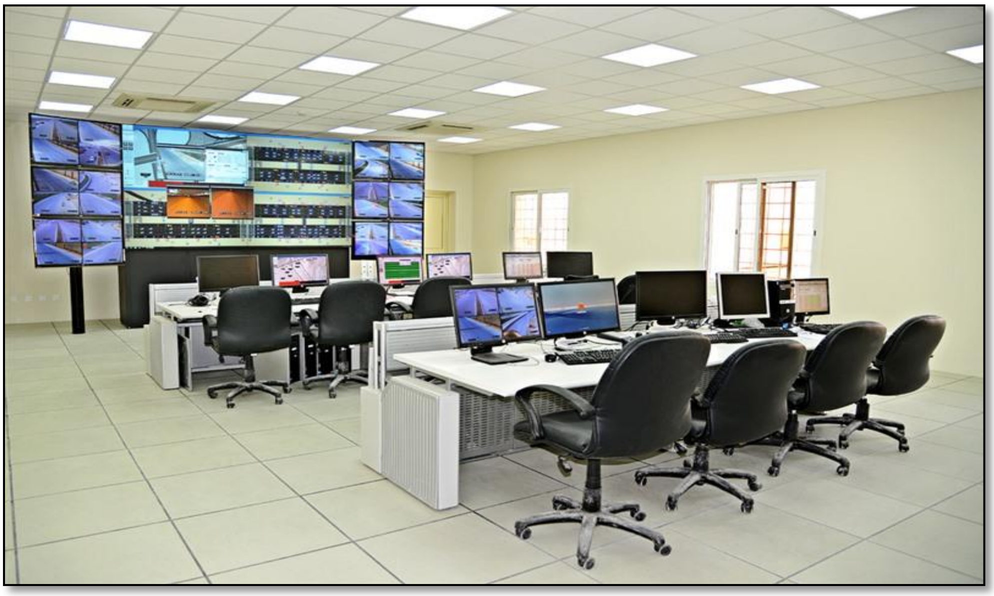


Figure 6.5 A Central Control Room in Riyadh

6.2.1 Traffic Data

The CCTV system is used to record the number of vehicles passing through a camera sensor point precisely with time information for the whole year. After processing these data, the CCR system generates data reports containing date and time of each point with camera source ID (monitoring location) and average speed and flow of vehicles on the roads. The traffic data set we obtained was recorded at 15-min basis over the period of 3 months. Table 6.1 displays sample of a data report generated by the CCR system.

Table 6.1: Sample of data recorded from Tunnel 1 on 1st January 2016

Start time	Source	Speed (km/h)	Vehicle count
2016-01-01 00:00:00	CAM_T1_EW_01	95.37	713
2016-01-01 00:00:00	CAM_T1_EW_02	95.55	752
2016-01-01 00:00:00	CAM_T1_EW_03	97.13	721
2016-01-01 00:00:00	CAM_T1_EW_04	89.45	772
2016-01-01 00:00:00	CAM_T1_EW_05	97.91	767
2016-01-01 00:00:00	CAM_T1_EW_06	90.99	765
2016-01-01 00:00:00	CAM_T1_EW_07	79.49	746
2016-01-01 00:00:00	CAM_T1_EW_08	95.63	785
2016-01-01 00:00:00	CAM_T1_EW_09	95.16	783
2016-01-01 00:00:00	CAM_T1_EW_10	94.77	630
2016-01-01 00:00:00	CAM_T1_WE_01	92.35	761
2016-01-01 00:00:00	CAM_T1_WE_02	85.37	772
2016-01-01 00:00:00	CAM_T1_WE_03	96.55	800
2016-01-01 00:00:00	CAM_T1_WE_04	84.57	846
2016-01-01 00:00:00	CAM_T1_WE_05	85.72	731

6.2.2 Emissions Data

Detailed information regarding the CO emission that was present on road tunnels at Al-Urubah and Abu Bakr Al-Siddiq roads were collected from ADA's database. In this thesis, a period of 3 months was considered for analysis. The

CO level and air velocity reports provided by ADA contained comprehensive information, as shown in Table 6.2 and Table 6.3.

Table 6.2: Sample of air velocity data recorded from Tunnel 3 on 1st February 2016

Date/Time	Point	Remote	Message	Description
1/2/2016 3:13:46.242	AVC_T3_NS_02_AirVelocity	PLCMAIN_T3rtu	Value = 8.00999481860094 m/sec	AirVelocity
1/2/2016 3:14:56.191	AVC_T3_NS_02_AirVelocity	PLCMAIN_T3rtu	Value = 7.88999482307133 m/sec	AirVelocity
1/2/2016 3:15:16.220	AVC_T3_NS_02_AirVelocity	PLCMAIN_T3rtu	Value = 8.06999481636569 m/sec	AirVelocity
1/2/2016 3:15:31.418	AVC_T3_NS_02_AirVelocity	PLCMAIN_T3rtu	Value = 7.99999481897345 m/sec	AirVelocity
1/2/2016 3:16:01.126	AVC_T3_NS_02_AirVelocity	PLCMAIN_T3rtu	Value = 8.13999481375799 m/sec	AirVelocity
1/2/2016 3:54:11.281	AVC_T3_NS_02_AirVelocity	PLCMAIN_T3rtu	Value = 10.0199947437214 m/sec	AirVelocity
1/2/2016 3:59:02.351	AVC_T3_NS_02_AirVelocity	PLCMAIN_T3rtu	Value = 9.9399947467017 m/sec (HIGH state)	AirVelocity
1/2/2016 3:59:47.153	AVC_T3_NS_02_AirVelocity	PLCMAIN_T3rtu	Value = 10.009994744094 m/sec (HIGH-HIGH state)	AirVelocity
1/2/2016 4:02:06.650	AVC_T3_NS_02_AirVelocity	PLCMAIN_T3rtu	Value = 9.9399947467017 m/sec (HIGH state)	AirVelocity
1/2/2016 4:17:27.930	AVC_T3_NS_02_AirVelocity	PLCMAIN_T3rtu	Value = 10.0199947437214 m/sec	AirVelocity
1/2/2016 4:26:03.222	AVC_T3_NS_02_AirVelocity	PLCMAIN_T3rtu	Value = 9.96999474558413 m/sec	AirVelocity

The collection time steps are not constant, but are different from time interval. This is because of the fact the air monitoring devices record the information only when there is a change in sensor reading. The information of the emissions report includes CO level, date, air speed, time of the day and device ID.

Table 6.3: Sample of CO level recorded from Tunnel 3 on 1st January 2016

Date/Time	Point	Remote	Message	Description
1/1/2016 0:03:16.077	CO_T3_NS_02_COLevel	PLCMAIN_T3rtu	Value = 0.0899999966471876 ppm (LOW state)	CO Level
1/1/2016 0:03:21.198	CO_T3_NS_02_COLevel	PLCMAIN_T3rtu	Value = 1.22999995417823 ppm (NORMAL state)	CO Level
1/1/2016 0:04:11.557	CO_T3_NS_02_COLevel	PLCMAIN_T3rtu	Value = 0.0899999966471876 ppm (LOW state)	CO Level
1/1/2016 0:04:16.665	CO_T3_NS_02_COLevel	PLCMAIN_T3rtu	Value = 3.92999985359386 ppm (NORMAL state)	CO Level
1/1/2016 0:05:01.976	CO_T3_NS_02_COLevel	PLCMAIN_T3rtu	Value = 0.0899999966471876 ppm (LOW state)	CO Level
1/1/2016 0:05:06.885	CO_T3_NS_02_COLevel	PLCMAIN_T3rtu	Value = 1.25999995306063 ppm (NORMAL state)	CO Level
1/1/2016 0:05:22.420	CO_T3_NS_02_COLevel	PLCMAIN_T3rtu	Value = 0.0299999988823959 ppm (LOW state)	CO Level
1/1/2016 0:05:27.748	CO_T3_NS_02_COLevel	PLCMAIN_T3rtu	Value = 2.81999989494521 ppm (NORMAL state)	CO Level
1/1/2016 0:05:53.845	CO_T3_NS_01_COLevel	PLCMAIN_T3rtu	Value = 0.119999995529583 ppm (LOW state)	CO Level
1/1/2016 0:05:58.803	CO_T3_NS_01_COLevel	PLCMAIN_T3rtu	Value = 0.479999982118334 ppm (NORMAL state)	CO Level
1/1/2016 0:10:47.832	CO_T3_NS_02_COLevel	PLCMAIN_T3rtu	Value = 0.0899999966471876 ppm (LOW state)	CO Level

In order to use these emissions data in the research analyses, an aggregation approach is performed to obtain the average the value of CO level and air speed based on 15-min basis to compatible with traffic data. Therefore, it became possible to integrate the emissions data files with the traffic data files easily based on the unique time interval. It is important to note that the large emission data sets need to be analysed. Therefore, the first step is proper filtering of the given dataset, e.g., excluding all data recorded during maintenance operations. In addition, all abnormal or improper traffic data records, such as the error resulting from devices or sensors itself, were excluded as well. The average CO concentration and air speed were calculated for each emissions and air monitoring devices after the filtering process. These data were aggregated for every 15-minute interval and combined with traffic data into one data set. These steps facilitate the integration of the emissions data with the corresponding traffic flow conditions, and consequently exploring the relationships between them.

6.3 Methodology

As mentioned earlier in Chapter 4, the total road emission (E_t) is defined as *"the mass of a specific pollutant emitted to the atmosphere associated to the vehicles activities on the road of given time".* In tunnel studies, total emission can be evaluated by applying the concept of mass balance inside the tunnel. The following are the considered assumptions:

- The first assumption is that the air velocity in the tunnel is constant for each test (or time interval).
- The second assumption is the concentration difference between sampling points located at the boundaries of each outlet and inlet of the tunnel represents the mass produced from specific pollutants like vehicle emissions (Hwa et al., 2002; Jamriska et al., 2004).

Thus, the mean air velocity in the tunnel (V_{air}) can be estimated from the average air speed across the tunnel as follows:

$$V_{air} = \sum \overline{v_{air}} \times A \tag{6.37}$$

where $\overline{v_{air}}$ is the average measured airflow rate across the tunnel and A is cross section area of the tunnel.

The total CO emission rate emitted from vehicles passing between two cross-sections from tunnel inlet to outlet can be determined as:

$$E_t = V_{\ air} \times (\overline{CO_{out}} - \overline{CO_{in}}\ ) \tag{6.38}$$

where $\overline{CO_{out}}$ and $\overline{CO_{in}}$ represent average concentrations of the CO emission measured at the air outflow cross-section and air inflow cross-section respectively.

In addition, traffic emissions factors (E_f) are also one of the main tools for air quality assessment of traffic decisions and control strategies. The emission factor (emitted mass per vehicle and km) is defined as *"the total mass of a specific pollutant emitted by vehicle to the air for a given time related to total distance travelled".* In this study, the average E_f can be obtained from road tunnel using (6.39) by knowing the number of vehicles passing through the tunnel during each period of time t; and the distance between tunnel two cross-sections L (Hsu et al., 2001; Jamriska et al., 2004):

$$E_f = \frac{E_t}{N \times L} \tag{6.39}$$

Above proposed methodology is applied on field data gathered from road tunnels in Riyadh during 3 months (January, February and March) in 2016. This data are used to explore the macroscopic relationship between MFD and vehicular emissions as discussed in the following section.

6.4 Results and Analysis

This section describes the trend between E_t and the average aggregated flow, density and speed of vehicles in the road tunnels. Furthermore, the relation between emissions factor E_f and these traffic parameters are discussed. Finally, the correlation analyses between MFD and traffic road emissions are investigated.

6.4.1 Traffic and Total CO Concentration Trends

As mentioned earlier, the two databases (traffic and emissions) were combined together for exploratory analyses to investigate the trends between traffic and emission concentration followed by data aggregation of CO level and air speed. These analyses investigate the data before examining the correlation between the MFD and road emissions. Figure 6.6, Figure 6.7 and Figure 6.8 represent traffic flow, density and speed, and resulting CO concentration for 24 hours of a day of three months.

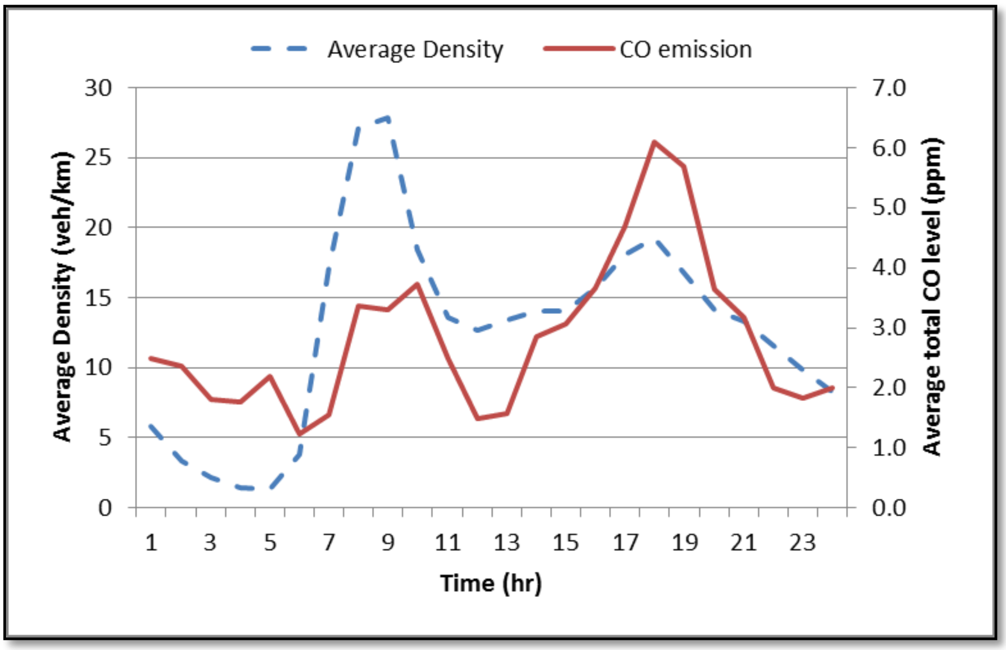


Figure 6.6: Traffic density and CO level variation for a full day

Figure 6.6 represents CO emission with traffic density for a complete one day. Generally, CO emission follows the trends of traffic density on road. As shown in Figure 6.6, the morning peak occurs between 7 AM to 9 AM, while the evening peak happens between 4 PM to 8 PM. The traffic density in morning peak is 40% higher than in the evening. Even though, CO emission keeps the standard trends, CO concentration at morning peak is 45% lesser when comparing to evening peak. This is because of the fact that the number of heavy-duty vehicles in the morning is lesser than evening. This is imposed by the traffic regulation in Riyadh city that prohibits heavy vehicles, mainly trucks, from entering into the city in between 9 AM to 1 PM noon. However, the result shows that there is a positive and strong relation between the total emission released from vehicles and average traffic density. Obviously the increased average traffic density results in the increased total emission level.

Figure 6.7 represents CO emission with traffic speed over the period of one whole day. It is observed that CO emission follows the inverse trend of traffic speed on road. The total emissions increase with the decrease in average network speed. The trend between CO emissions and traffic speed from field data support the finding in Chapter 4. The analysis resulted from Orlando network has showed similar trend to field data. Generally, there is a negative relation between the average network speeds and total emission. In addition, the traffic speed in evening peak is 33% higher than morning peak. This is because of the fact that number of vehicles traveling in morning is higher. In other words, evening peak has less traffic congestions even though heavy vehicles are allowed to travel within the city.

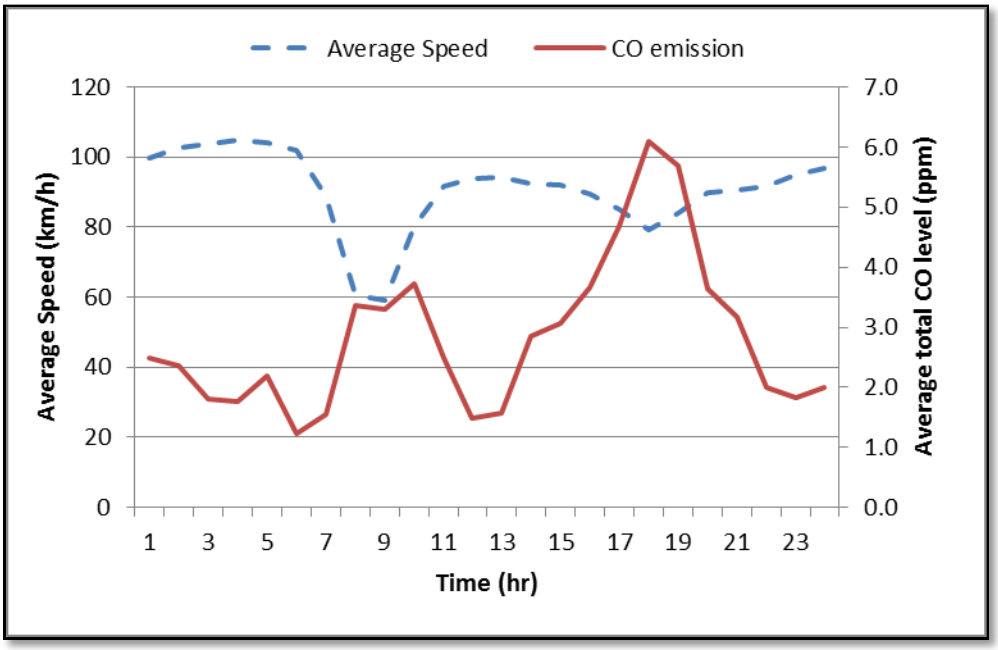


Figure 6.7: Traffic speed and CO level variation for a full day

Figure 6.8 presents CO emission with daily traffic flow. It is obvious that CO emission and traffic speed at network wise does not follow any clear trends.

As shown in the Figure 6.8, the traffic flow remains fairly consistent above 1100 veh/h per lane from 7 AM in the morning to 9 PM in the evening. However, CO concentration is fluctuating during this time. The cause of this is the variation of traffic density and speed besides different vehicle fleet due to absence of heavy vehicles in morning.

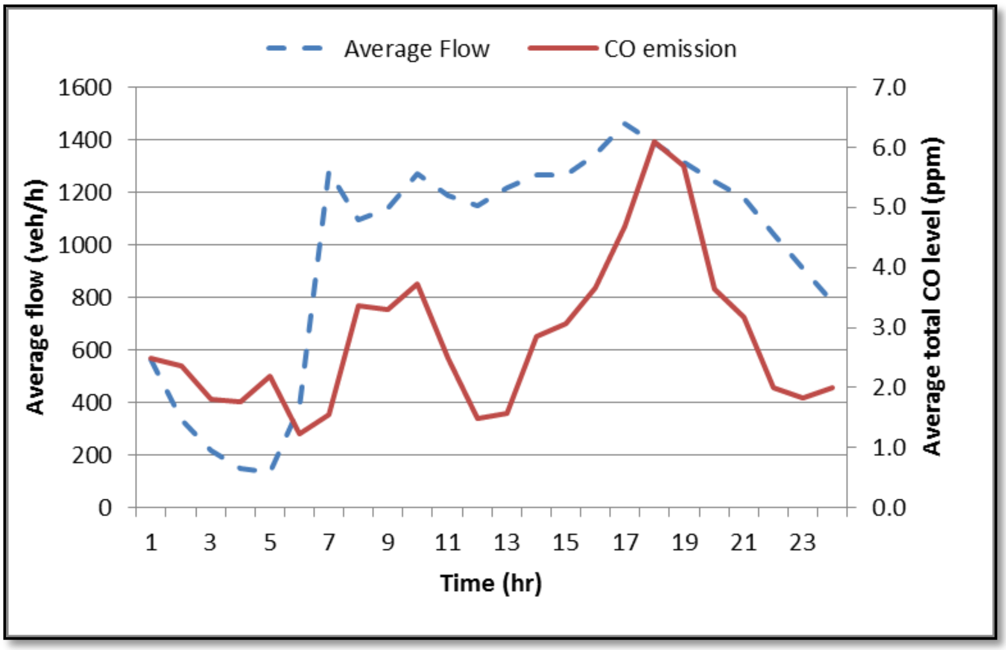


Figure 6.8: Traffic flow and CO level variation for a full day

Further investigations are still needed to explore the impact of the traffic flow on CO emissions. For insistence, a sensitivity analysis is suggested to find out the effect of traffic flow on CO emissions, taking into account the impact of the percentage of heavy vehicles during data collections. Finally, because of the absence of vehicle fleet data from gathered field data, it is not possible to perform such analysis.

6.4.2 Relation between Macroscopic Traffic Variables and CO Emissions Factor

In this section, the CO emissions factor is calculated for single vehicle traveling through traffic tunnels T1, T2 and T3. The emissions data were aggregated for every 15-min time interval to obtain average values of CO concentration and air flux with respect to associated traffic data from same tunnels. Then relation (6.39) is applied to determine the emissions factor of CO pollutant. This analysis investigates the relation between the MFD parameters and CO concentration rate emitted with respect to traffic conditions. The Figure 6.9, Figure 6.10 and Figure 6.11 represent the relationships between traffic flow, density and speed, and resulting CO emission rate for total vehicle-kilometres travelled. These figures reflect the actual situation from real field data from studied tunnels in Riyadh.

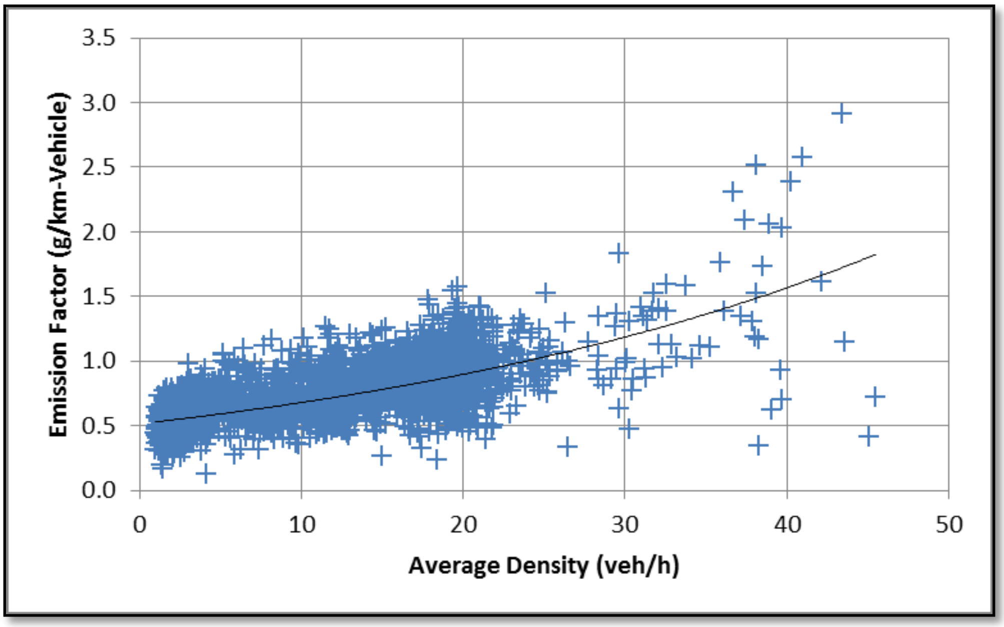


Figure 6.9: Average traffic density vs. CO emission factor

Generally, the increased number of vehicles passing through tunnels increases the amount of total CO emission released per vehicle per unit of distance travelled. It can be observed from Figure 6.9 that there is a positive relation between the emissions factor with both average density and average flow on roads. As shown in Figure 6.9, the vehicle traveling in congestion emits three times more emission as compared with traveling in free flow state. For example, the amount of CO emission per km increased from 0.5 to 1.5 in on the average due to changed traffic conditions, especially density. In addition, the figure shows that high scatter in emission levels per vehicle exist when the percentage of congestion is increased.

Figure 6.10 represents CO emission factor with traffic flow. In general, an increase in traffic flow slightly increases the vehicular emissions. The result show that the amount of CO emission per km increased from 0.5 to 1 on average with respect to increasing traffic flow. In addition, high scatter in emission levels from vehicles appear near maximum network traffic flow.

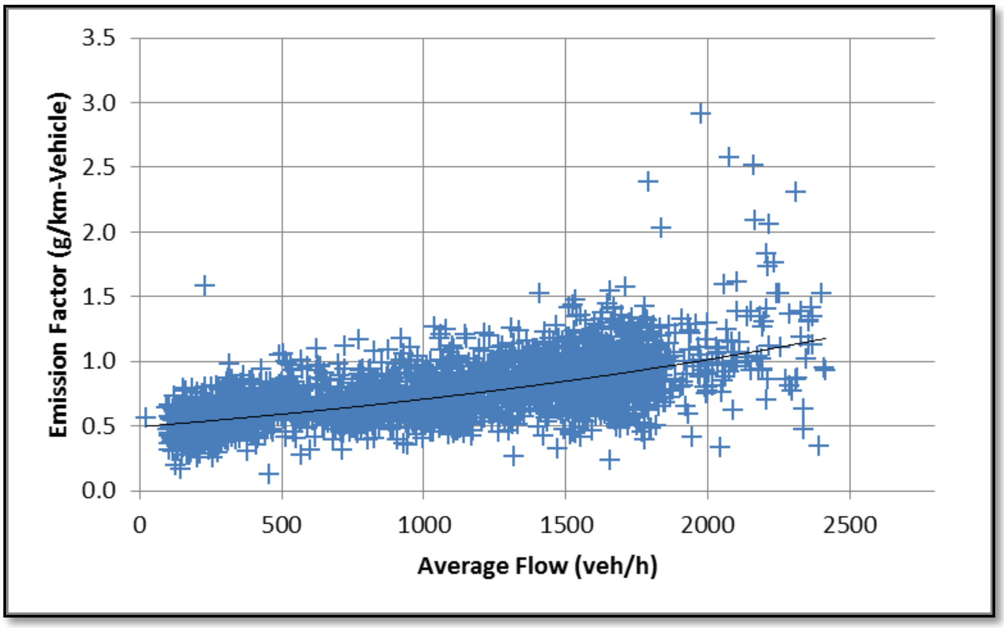


Figure 6.10: Average traffic flow vs. CO emission factor

On the other hand, the vehicular emission per km travelled is negatively associated with average traffic speed. Figure 6.11 shows significant improvement in CO emission level associated with average traffic speed in network. The quantity of CO emission per km travelled dropped from 2.5 to 0.5 on average with respect to increased traffic speed. A higher level of scatter in vehicles emission levels appear at lower speed, especially below 70 km/h.

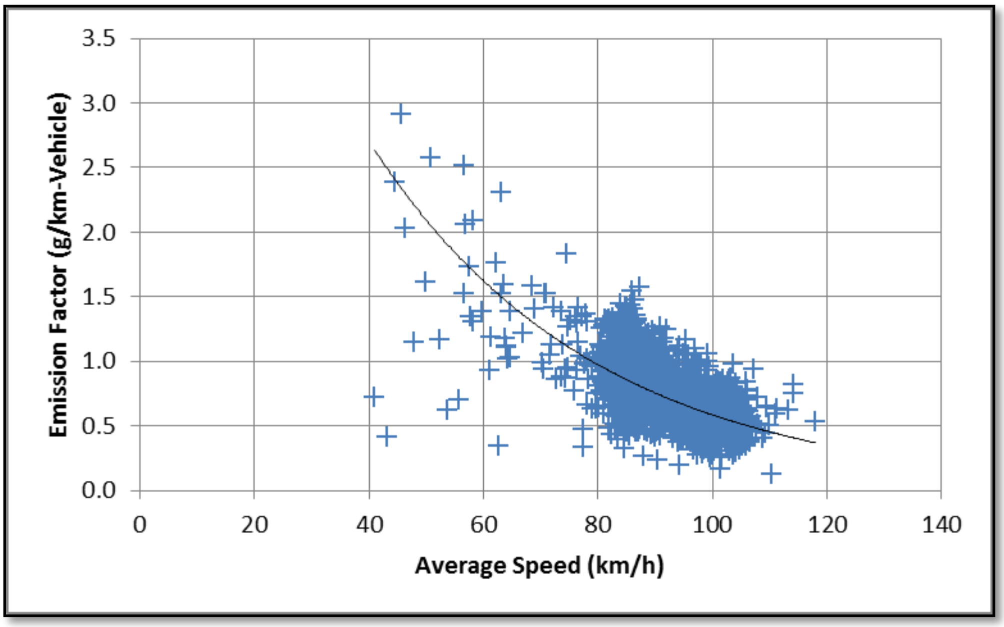


Figure 6.11: Average traffic speed vs. CO emission factor

6.4.2.1 *The Correlation Test*

This section aims to observe the correlations between the MFD and amount of total vehicular emission per unit of distance travelled. The primary regression analysis is applied to data collected from road tunnels in Riyadh. Linear regression is performed between average traffic flow, density and flow with CO emission factor. Figure 6.12 shows the existence of the MFD from tunnels data in Riyadh, and characterises the traffic situation in each case. The over saturated regime does not appear in these tunnels since the Al Urubah road and Abu Bakr Al Siddiq road are controlled by the CCR of ArRiyadh Development Authority.

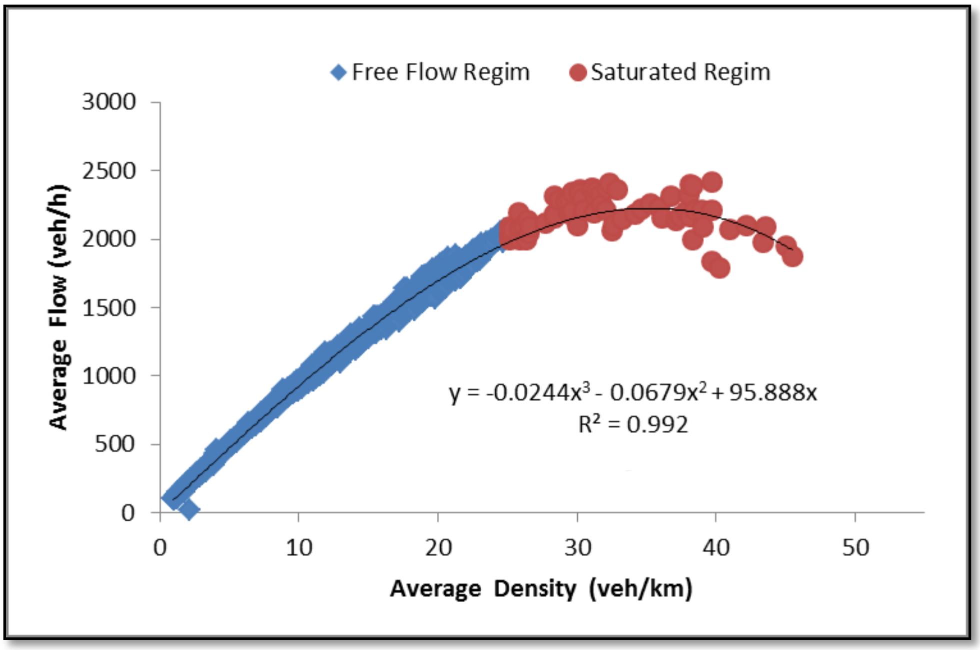


Figure 6.12: The MFD from tunnels data in Riyadh city

Table 6.4 represents that the correlation coefficients were computed at each individual but different traffic state (free flow and saturated) and the combined case as well. The results depict strong correlations between the MFD parameters (q, k and v) with CO emission factor for free flow condition. The correlation values were 0.669, 0.672 and -0.639 for average network flow, density and speed respectively. These correlations are valid for traffic speed more than or equal to 80 km/h. However, the relation generally becomes fairly correlated for speed range between 40 km and 80 km especially for saturated conditions. While the correlations between CO emission factor and average flow changes behaver from positive to negative correlation. The linear relations follow similar directions in both traffic conditions between average speed or density and emission factor, and are fairly less strong at saturated regime. Overall, these results are consistent with the results obtained from simulated data for Orlando network in Chapter 4.

Table 6.4: The correlation between traffic variables and CO emission factor

Traffic Status	Average Flow	Average Density	Average Speed
Free Flow	*0.669*	*0.672*	*-0.639*
Saturated	*-0.130*	*0.394*	*-0.435*
Pooled	*0.657*	*0.684*	*-0.666*

Although, the conclusion from this analyses cannot be used as a robust relation to estimate the impact of traffic conditions on vehicular emission, due to lack of a definitive relationship. However, this study has revealed the existence of clear relation between the macroscopic fundamental diagram and vehicular emissions in real-world traffic conditions. Thus, there is a potential of future work to understand the relationship between the shape of the MFD and road emissions rate in urban network.

6.5 Further Research Directions

The air quality monitoring of Riyadh network in Saudi Arabia has become one of the main duties of the ArRiyadh Development Authority (ADA). In 2013, the ADA started a new project called '*ArRiyadh Air Quality Management Project*' in order to devise efficient strategies for air quality management and enhance effective policy decision making for the city of Riyadh. The project aimed to identify the key pollutants within the city and to classify their sources in a robust way, which will definitely support emission reduction strategies in pursuit of Riyadh air quality ambitions.

To achieve high quality monitoring data, ADA have introduced 16 new monitoring stations in Riyadh (see Figure 6.13 for locations and Figure 6.11 for a sample monitoring station) with one mobile monitoring station (see Figure 6.13), in addition to the five pre-existing stations installed more than ten years ago requiring maintenance and upgrading with the new equipment.

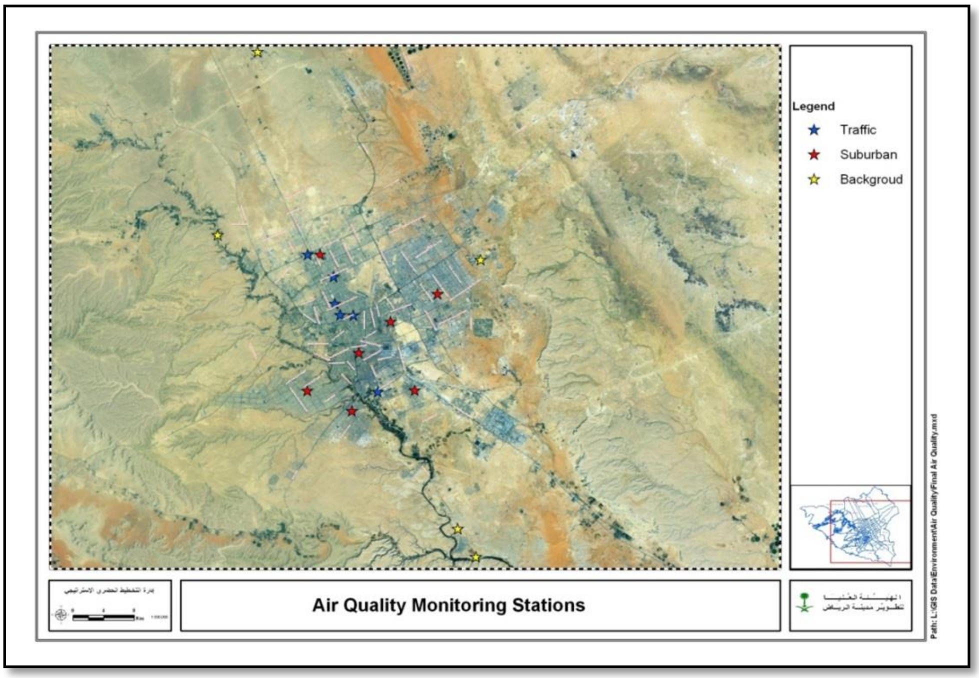


Figure 6.13: Locations of new background, suburban and traffic monitoring stations for Riyadh network

Figure 6.14: Sample of monitoring station on the side of a road or residential area

Figure 6.15: A mobile monitoring station used in Riyadh air quality management project

As shown in Figure 6.13, 4 monitoring stations are background sites and 7 stations are reserved for suburban monitoring, while 5 stations have to quantify the pollution from road traffic. All of these monitoring stations were well utilised to implement a city scale air quality management and information system as well as to provide supporting data sets for scientific research. Each of the stations measured a range of air pollutant types using automatic gas and particulate analysers (see Table 6.5).

The background stations represent the air quality data that has not been influenced by the pollutants emitted within the city. These stations are located outside of Riyadh city and provide a good comparison to define the contribution to air pollutants from the city itself. While suburban monitoring stations are located in the most densely populated residential areas of Riyadh. These monitoring stations provide excellent representation of air pollutant concentrations in Riyadh city as a spatial assessment. The traffic related monitoring stations provide measurements to determine the contributions of motor vehicles to air pollution in the Riyadh city. These monitoring stations are chosen to be located at distance between 1 m and 10 m from busiest roads in the city. The mobile monitoring station targets specific emission sources for short term air monitoring such as industrial or power stations sources.

Table 6.5: Recommended pollutants to be monitored in each site

Site Category	**Pollutants to be Monitored**
Background	*PM10 , NOX , SO2 , O3 , benzene, lead*
Suburban	*PM10 , PM2.5 , NOX , SO2 , CO, H2S, O3 , benzene, lead ,NMHC*
Mobile	*PM10 , PM 2.5 , NOX , SO2 , CO, O3*

The 'ArRiyadh Air Quality Management Project' is expected to complete in early 2018 and the data will be ready for governmental use as well as for scientific research purposes after 3 months of pilot operation. In addition, traffic speed, density, flow and vehicle type are monitored as well. The data sets gathered from these different monitoring stations with relevant traffic data provide an opportunity to study the impacts of traffic activities in Riyadh city and to link this effect with traffic conditions. So, it has become vital to investigate the analysis with more robust data in order to support the understanding the relationship between the macroscopic fundamental datagram parameters and the total emissions from real-world traffic data in Riyadh city. In fact, the availability of the above data enables a researcher to consider the effect of vehicle component (i.e., heavy-duty or light-duty) and background concentrations in order to provide robust assessment of traffic-related air pollution in Riyadh.

6.6 Summary

The relation between MFD parameters and road emissions has been investigated in detail based on real-world field data collected from three different road tunnels in Riyadh in Saudi Arabia.

Firstly, a trend analysis was conducted to investigate how CO level varies with the change of traffic parameters over the time of the day. The findings are summarised as follows:

- The total CO level tends to increase with an increase in the traffic density,
- The total CO level tends to decrease with an increase in the traffic speed,
- There no clear trend between the total CO levels with traffic flow.

In addition, the relation of MFD parameters and the emissions factor of CO pollutant were explored. A correlation analysis was used to determine relation between traffic flow, density and speed, and resulting CO emission rate per vehicle per unit of distance travelled. The results are summarised as:

- A strong correlation exists between total CO emissions released per vehicle per unit of distance travelled with the MFD parameters (q, k and v) at free flow condition. A positive correlation was observed with flow and density while it was negative with speed.
- For saturated conditions, the relationship generally becomes fairly correlated with average density and speed.
- Vehicular emission per km travelled is positively associated with average traffic flow at free flow regime, while the opposite (negative correlation) in saturated regime.

Finally, the existence of clear relation between MFD and vehicular emissions in real world has been revealed. In general, the real field data results are consistent with the results from simulated data for Orlando network as in Chapter 4. The major conclusion of this chapter is that the MFD model can be utilised effectively to the network-wide emissions assessment from real field data.

Chapter 7.

Conclusion and Future Work

An innovative methodology/framework has been proposed in this thesis for the effective application of well-known two-fluid model (TFM) on road emissions of urban networks to estimate the network-wide traffic-related emissions state at macroscopic level. This is demonstrated by developing an analytical model that illustrates the relationship between the parameters of the TFM and corresponding emissions of the traffic network. Hence the main contribution of this research study is the proposed hypothesis and consequently the formulation of a new model that estimates and evaluates the dynamic road emissions assessment at the network level in macroscopic manner. In addition, this study validates the feasibility of using the TFM to estimate vehicular emissions. The findings of the research are justified with two simulation experiments with two unique road networks. First network covers a part of Orlando downtown in United States, while the second network is artificial grid network with a number of roundabout intersections with uniform settings. Further investigations in this thesis were completed through empirical data collected from real case studies in order to discover the relation between the macroscopic fundamental diagram (MFD) properties (flow, density and speed) and road emissions.

7.1 Summary of the Thesis

The chapter-wise contributions of the thesis are summarised as follows:

Chapter 1 of this thesis is an introduction to this study, which briefly discusses the need of a new approach for air pollutions assessment at network-level.

Chapter 2 of this thesis presented the literature review in the relevant field of traffic and emissions modelling. This chapter is sub-divided into two sections. The first section reviewed the literature of fuel consumptions and vehicular emissions modelling, and summarised the main sources and type of vehicular emissions. Also, the factors that affect the transportation pollutants were explored followed by an overview of the vehicle emissions modelling based on the scale of the input variables. The second section is related to traffic flow modelling. The definitions of TFM and MFD are presented along with their application on network level modelling. The major aim of this this chapter was to identify the research gap and to present the value of this research in relation to previous studies.

Chapter 3 of this thesis described the development of a new proposed model to evaluate the traffic emission at large-scale networks. Firstly, this chapter presented motivation towards new method for network-wide emission estimation. Secondly, this chapter presented the assumptions and development approach of proposed model utilising the TFM to estimate the proportion of the time spent in cruising and idling (traffic variables) of each observation time steps. Moreover, federal Test Procedure (FTP) drive cycle's sets were used to measure the emission rate (emissions variables) associated with cruising and idling times. In addition, the novel proposed model is considered as a new application of the TFM in order to assess quality of traffic systems with respect to air pollutions.

Chapter 4 of this thesis demonstrated the application of proposed model to estimate the CO_2 emission rate for Orlando downtown network. The average emission factor (E_f), together with total emission rate (E_{totl}), from proposed model was found consistent with the simulated data that were obtained from second-by-second by micro-simulation. The comparison of the CO_2 factor measured from analytical modelling showed that was not significantly different statistically with simulations, and the observed error from the model was lower than 6.5% during the saturated state. This chapter concluded that the proposed emission model could be applied to large-scale networks, and provide alternative tool for the air quality assessment effectively.

Moreover, the result showed a positive correlation between the average density in the network and the emission factor (g/veh-km). As the number of vehicles increased in the network, the average vehicle emission factor also increased. Whereas the total emission rate (g/step-time) from traffic system increased with increasing number of vehicles in traffic network until the system's saturation and reached to the maximum output. Then the trend radically referred to the negative relationship and total emission gradually decreased when network density increased.

Chapter 5 of this thesis examined and validated the TFM to estimate the traffic flow parameter and traffic emission utilising the proposed emission model as discussed in chapter 3. This chapter presented results from the micro-simulation of a grid network with different levels of traffic density scatter by introducing various turning movements at the intersections. In addition, the results showed that more reliable parameters estimates of TFM could be obtained with the existence of a well-defined MFD on the network and the accuracy of the traffic parameters estimation decreased with increasing percentage of network heterogeneity.

The proposed model performed well and showed high accuracy of emission prediction in homogeneous network. Although there were no differences in road type, control and traffic demands; the level of traffic density scatter was found to be an important factor in prediction accuracy. Thus, during modelling the vehicular emission, it was necessary to distinguish between homogenous and non-homogenous regions, since the vehicle emission rate per unit distance travelled is generally sensitive to level of network heterogeneity. Furthermore, the results showed that the proposed model provided an approximation of total emissions within 5% of the estimates from the detailed microscopic emission analysis in the case of low scatter MFDs. On other hand, the proposed model appeared to be an underestimating of total CO_2 emissions, with significantly larger relative error approximately equal to 16% when traffic network performed under high level of heterogeneity.

In summary, the overall result from this chapter implies that vehicle emission rate per unit distance travelled is sensitive to level of traffic heterogeneity due to turning movements in addition to the level of congestion in urban road traffic network.

Chapter 6 of this thesis investigated the relation between MFD parameters and road emissions based on real-world field data collected from three different road tunnels in Riyadh in Saudi Arabia. A trend analysis was conducted to investigate how total CO level varies with the change of traffic parameters' level over the time of the day. The key findings are: the total CO levels tend to increase with an increase in traffic density, where the total CO level tends to decrease with an increase in traffic speed, while no clear trend between the total CO levels with traffic flow.

In addition, a correlation analysis was used to determine relation between traffic flow, density and speed, and resulting CO emission rate per vehicle per unit of distance travelled. The result showed the existence of clear relation between MFD and vehicular emissions (g/veh-km) in real world data. In general, the real field data results were consistent with the results from simulated data from Orlando network. Hence the major conclusion of this chapter is: '*the MFD model can be utilised effectively to the network-wide emissions assessment from real field*.

7.2 Future Research Directions

Although the results of the new methodology for emissions estimation at network-wide are promising; several limitations exist. To address some of thesis limitations, we offer several open research directions for future exploration as follows:

The Effect of Network Characteristics

In this study, the results from the traffic microscopic simulation of grid network with different level of heterogeneity have been discussed. However, further investigation is needed to discover the effect of different network characteristics on estimating network-wide emissions. For instance, network infrastructure (link capacity and number of lanes) and control (traffic signals and free flow speed). This may affect demand distribution across the network and cause an uneven distribution of density.

In addition, the MFD provides a better understanding of the role of changing network properties on general network performance. Thus, there is a potential of future work to understand the relationship between the shape of the MFD and road emissions rate in urban network.

The Effect of Performing Different Spatial Evaluations of Traffic Networks

It is important to discover the effect of network size (study area) and network partitioning techniques on proposed model accuracy. For instance, network partitioning utilising the spatial characteristic of the network density and the definition of well-defined MFD is suggested for further research in order to investigate how the spatial resolution of network is associated with the model accuracy in emissions estimations.

The Effect of Sampling Methodology

In this study, the traffic microscopic modelling of simulated network with full detailed trajectory files has been discussed. However, the detailed data of vehicles trajectories in real world are unknown and may require crushing time and money to collect such data. The effect of using different monitoring techniques on traffic parameters, such as sensors, probe vehicles and smartphone, and their impact on the accuracy emissions estimations need to be investigated. Dixit and Geroliminis (2015) have theoretically and empirically proven that with 30% of GPS data from cell phones, a reliable MFD and TFM of the network can be estimated.

Application with Real Data

The empirical studies using traffic and emission data, which reflect the real traffic situation, could contribute to strengthen the hypothesis on the applicability of proposed model in real world. This study has shown that the proposed model in chapter 3 is capable of evaluating the total emissions in large-scale networks by considering the average vehicles behaviour using simulation data. However, the real world is a complex system and the traffic and emissions data from real world do not offer very smiler quality such as simulation data. Thus, a better understanding of the properties of real traffic and emissions data could help effectively.

The Effect of Different Traffic Management and Control Strategies

Traffic engineers and policy makers are generally implementing different control types and settings in order to enhance the traffic network performance and minimise delay, such as dynamic signals timing, speed limits and congestion pricing as well as network boundary control and routing strategies. Therefore, further investigation is needed of the effects of these strategies to examine the capability of the proposed model of capturing the change on network road emissions before and after their application. Furthermore, this investigation is significant and could provide essential tools to examine the efficiency of these traffic management policies and conduct environmental impact assessment.

Integrating the Proposed Model to a Macroscopic Simulation Model

The dynamic traffic simulation program, VISSIM, has been used in this thesis to structure and evaluate the study networks after aggregating the results every 5-minute time step. However, this requires dealing with an extensive data of second-by-second of operating conditions for the individual vehicles (vehicle trajectories) and corresponding cost and time for data processing and storing. Therefore, further investigation is vital to understand the efficacy of macroscopic simulation model and their outputs of transportation parameters to air pollution assessment via our proposed model.

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APPENDIX A

Conventional Macroscopic Speed-Flow Models

- **The Greenshields Model**

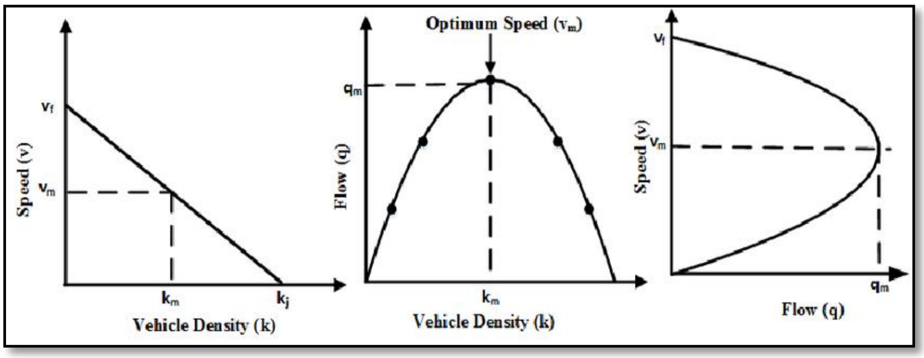

Figure A.1: The relation between flow, density and speed

The model was developed by Greenshields in 1935 to predict the liner trends between speed and density of uninterrupted traffic flow conditions of observed real data. This model is consider as simplest macroscopic traffic flow model as well as meet all boundary of traffic conditions (such as the density is zero when the flow is zero and the flow must be zero at jam density).This model has been used widely in traffic flow modelling since it is simple mathematical models. This relationship is expressed mathematically below:

$$v = v_f * \left(1 - \frac{k}{k_j}\right)$$

Where: v is the speed, v_f is the free speed, k is the density, $k_j$is the jam density.

- **Pipes' generalized model**

This model is generalised approach of the Greenshields Model by in introducing a new parameter (n). The model is shown by the following equation.

$$v = v_f * \left[1 - \left(\frac{k}{k_j}\right)^n\right]$$

- **The Greenberg Model**

The model was developed by Greenberg in 1959, the model is proposed by applying the fluid flow analogy on data from the Lincoln Tunnel in New York in order to build a logarithm to finger out the relation between speed and density. This model does not satisfy the boundary of traffic condition at the low density, the flow is goes to infinity when density is equal to zero. The model is shown by the following equation:

$$v = v_c * ln\left(\frac{k_j}{k}\right)$$

Where: v is the speed, v_c is the speed at capacity, k is the density, k_j is the jam density.

- **Underwood's exponential model**

The model was developed by Underwood in 1961 as an exponential model to analyse the relationship between speed and density. Although the goodness fit of this model is not high at congested conditions, this model generally has a better fit than the Greenshields and Greenberg models at free flow conditions. This model does not satisfy the boundary of traffic condition at jam density, when the speed approaches zero the model dose not yield a solution for the jam density .This relationship is expressed mathematically below:

$$v = v_f * e^{-k/k_c}$$

Where: v is the speed, v_f is the free speed, k is the density, $k_c$is the density at capacity.

- **The *Underwood* Model with Taylor Series Expansion**

Since the Underwood does not yield a solution for the jam density when speed approaches zero, the Taylor series is used to find a numerical approximation for the jam density.

$$v = v_f * e^{-k/k_c} = v_f \left(1 - \frac{k}{k_c} + \frac{k^2}{2k_c^2} - \frac{k^3}{6k_c^3} + \frac{k^4}{24k_c^4} - \frac{k^5}{120k_c^5} + \cdots\right)$$

Taking up the expansion to third degree of k yields:

$$v = v_f * e^{-k/k_c} = v_f \left(1 - \frac{k}{k_c} + \frac{k^2}{2k_c^2} - \frac{k^3}{6k_c^3}\right)$$

Where: v is the speed, v_f is the free speed, k is the density, $k_c$is the density at capacity.

- **The Drake Model (Bell-Shaped Curve Model)**

This model was developed by Drake in 1961 when he studied all existence macroscopic traffic models at that time and none of them was significant from statistical point of view. He used speed and flow data to estimate the density, fitted to the speed vs. density function then transformed it to speed vs. flow function. Drake approach resulted in better fit then

Underwood model for uncongested conditions, however, both models fails to provide a good fit for congested conditions. This model is expressed mathematically below:

$$v = v_f * exp\left[-\frac{1}{2\left({}^{k}/_{k_c}\right)^2}\right]$$

- **The Drake Model with Taylor Series Expansion**

In this model, the Taylor series is used to find a numerical approximation for the jam density as conventional Drake model does note yield a solution.

$$v = v_f\left(1 - \frac{k^2}{2k_c^2} + \frac{k^4}{8k_c^4} - \frac{k^6}{48k_c^6}\right)$$

- **The Polynomial Models**

The speed vs. density relationship can be expressed mathematically on term of n degree polynomial equation as below:

$$v = v_f + b_1k + b_2k^2 + b_3k^3 + \cdots$$

APPENDIX B

Graphical Representation of the two-fluid model

- **1st scenario**

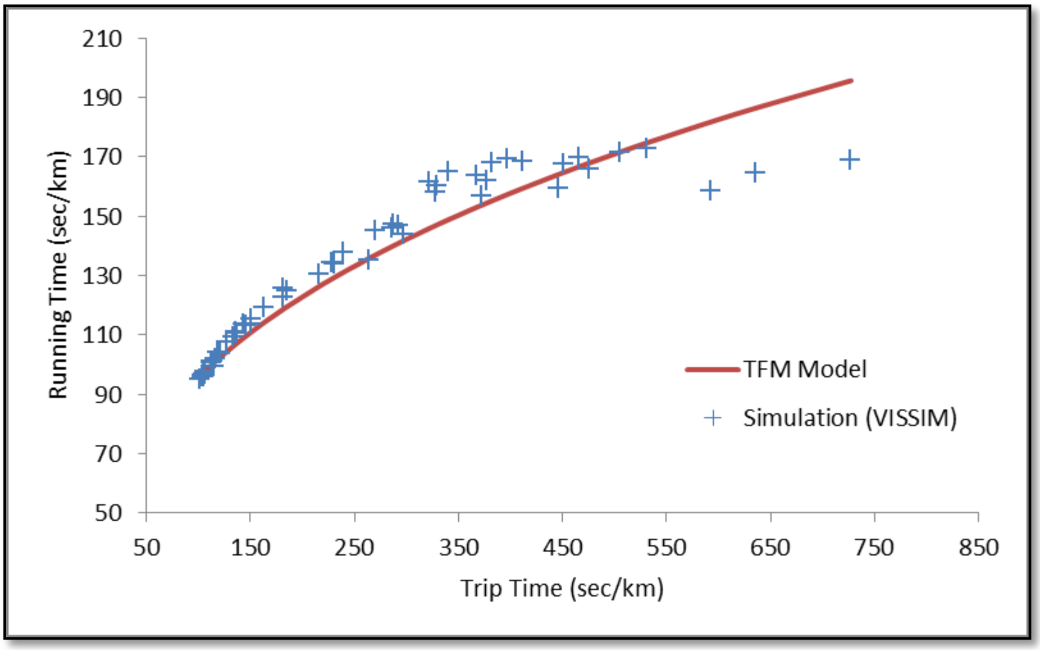

Figure B.1: The trip time vs. the running time – a comparison between estimated from TFM and the simulated results

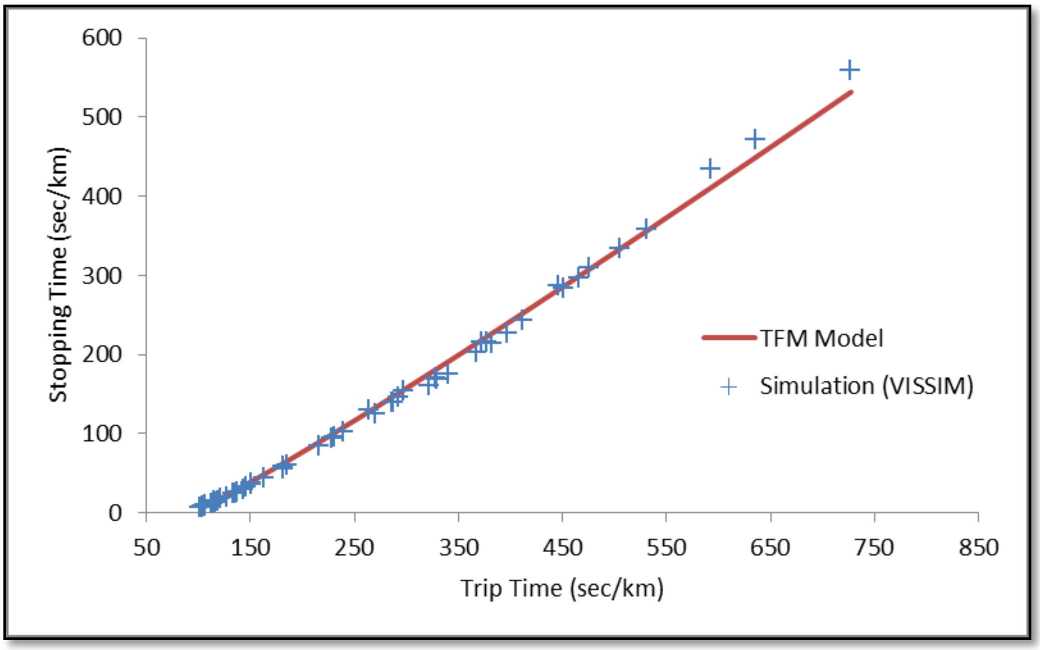

Figure B.2: The trip time vs. the stopping time – a comparison between estimated from TFM and the simulated results

- **2nd scenario**

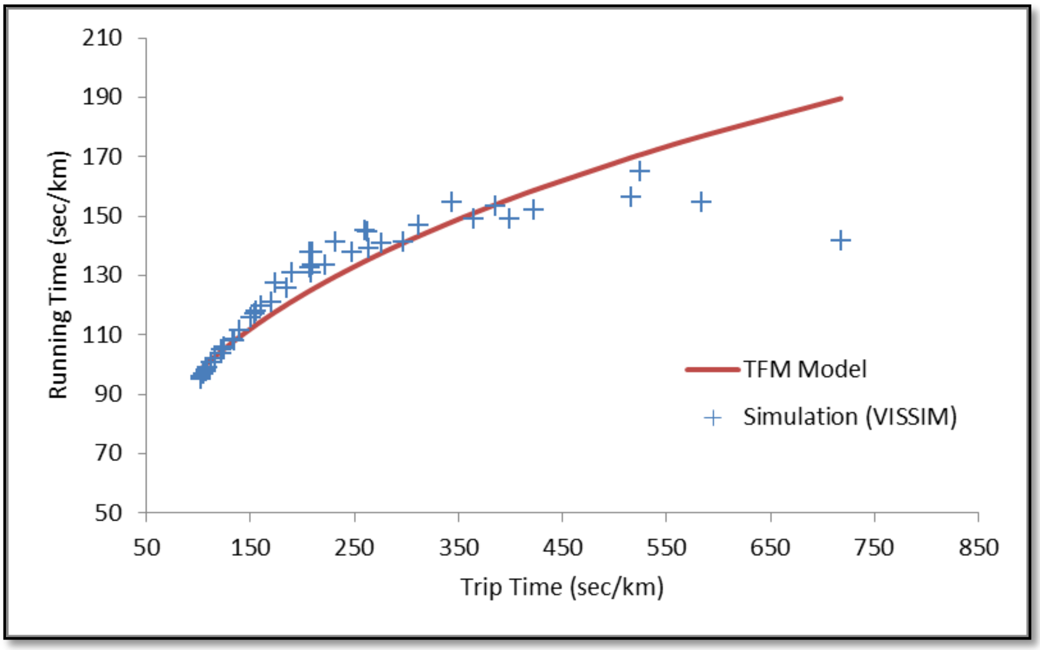

Figure B.3: The trip time vs. the running time – a comparison between estimated from TFM and the simulated results

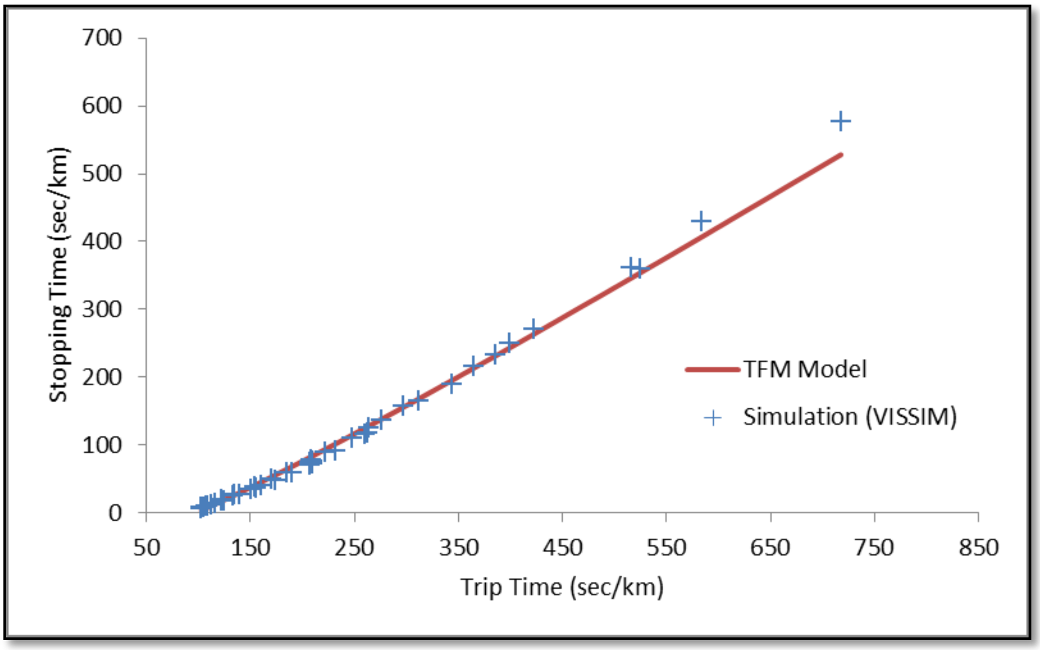

Figure B.4: The trip time vs. the stopping time – a comparison between estimated from TFM and the simulated results

- **3rd scenario**

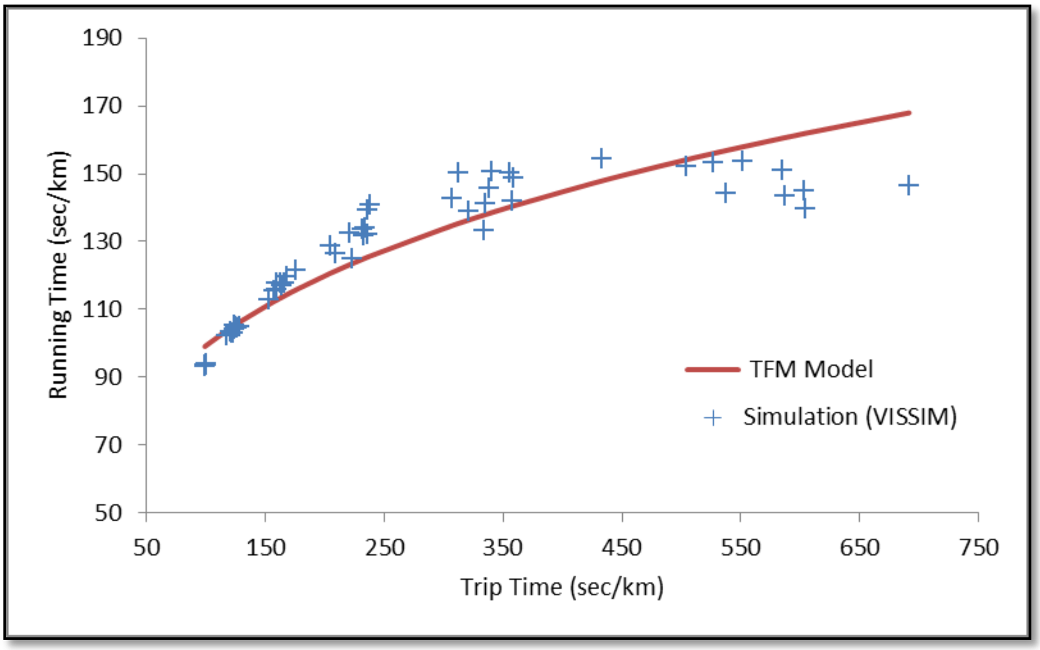

Figure B.5: The trip time vs. the running time – a comparison between estimated from TFM and the simulated results

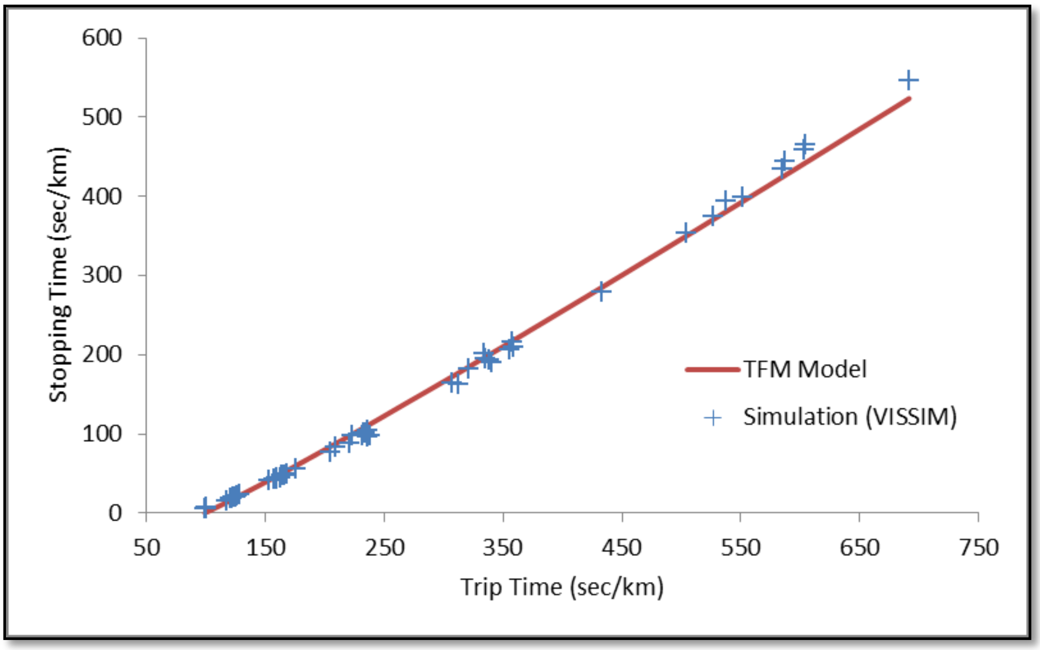

Figure B.6 The trip time vs. the stopping time – a comparison between estimated from TFM and the simulated_result